

A Structural Model of the Unemployment Insurance Take-up

Sylvie Blasco*
GAINS, University of Aarhus,
CREST and IZA

François Fontaine†
BETA-CNRS,
LMDG and IZA.

January 2012 - IN PROGRESS‡

Abstract

A large fraction of the eligible workers do not claim the unemployment insurance when they are unemployed. This paper provides a structural framework to identify clearly, through the estimates, the economic mechanisms behind take-up. It incorporates take-up in a job search model and accounts for the determinants of claiming, especially the level of the unemployment benefits and the practical difficulties to make a claim. It provides a simple way to model selection into participation and sheds new light on the link between the job search and the claiming efforts. We estimate our model using a unique administrative dataset that matches a linked employer - employee data and the records of the national employment agency.

Keywords: Unemployment Insurance Take-up, Job Search

JEL Classification numbers: J64, J65, C41

*Address : Université du Maine, Av. Olivier Messiaen, 72085 Le Mans Cedex 9, France ; Email: sylvie.blasco@univ-lemans.fr

†University of Nancy 2, Email: francois.fontaine@univ-nancy2.fr.

‡We thank Jesper Bagger, Sebastian Buhai, Sam Kortum, David Margolis, Dale Mortensen, Fabien Postel-Vinay, Jean-Marc Robin, Chris Taber and participants at the Tinbergen Institute internal seminar, CREST-INSEE, Nancy and Royal Holloway seminars, the ESEM conference, the AFSE, IZA-Labor Market Policy Evaluation, LMDG, T2M workshops for comments and discussions. This is a preliminary version of the paper, the readers are invited to check on the authors' websites for newer versions.

1 Introduction

Unemployment insurance (UI hereafter) has been designed to insure workers against the loss of income. However, like most welfare benefits (Currie [2006], Hernanz *et al.* [2004]), the take-up among eligibles is far from 100%. The unemployment insurance take-up rate is estimated to range between 40% and 70% in the US (Blank and Card [1991], Anderson and Meyer [1997], McCall [1995]) and between 60% and 80% in Canada and the UK (Storer and Van Audenrode [1995], DWP [2008]). Theoretical studies and empirical evaluations of the UI system usually ignore this problem and assume that all eligible workers receive benefits (see Kroft [2008] for a notable exception). However, the empirical low take-up rates question this assumption and a study of the efficiency of the actual UI systems should take this empirical evidence seriously. For that purpose, it is first crucial to investigate the determinants of the take-up. This paper provides and estimates a structural model to address this issue.

It builds on the existing welfare benefits take-up literature (see Moffit [1983] and Currie [2006] for a recent survey). In our framework, take-up is the result of a utility-maximizing decision which accounts for the gains of participating in the UI system (the expected unemployment compensation or the job search assistance) and the expected costs which depend on the practical difficulties to make a claim, which are modeled as frictions in the claiming process.

An important feature of our model is its ability to explicitly take into account the link between the job search activity and the take-up behavior. This is crucial to estimate the impact of the take-up rate on the cost of unemployment. Indeed, some eligibles are not observed as receiving unemployment benefits because they leave unemployment very quickly. If a worker expects a relatively low unemployment duration and faces claiming frictions, he has few incentives to participate in the UI system. The existing literature does not account for this link explicitly. Moreover, it uses static choice models (McCall [1995], Blank and Card [1991], Anderson and Meyer [1997]), while we argue that one must take into account the duration of the insured and uninsured unemployment spells. In terms of welfare cost, it is crucial to look at the duration of the non insured unemployment spell along with the take-up rate *per se*. Especially, we show that some workers receive unemployment benefits after a relatively long period of uninsured unemployment. For these workers, the existing frictions in the claiming process are very costly.

We provide a dynamic framework in which we model both the worker's job search and his effort to collect information to file for UI benefits. We go beyond the idea of a binary choice between claiming or not by introducing the idea of claiming effort. This allows us to account for temporary non take-up, *i.e.* to study the distribution of durations without receiving benefits, and not to limit the analysis to the share of the eligible population which receives the unemployment insurance. Interestingly, our model exhibits selection in the participation in the UI system and substitution

between job search activities and the claim for the unemployment compensation.

Rather than estimating a reduced-form hazard rate model, we proceed to a structural estimation using a unique administrative dataset that follows individuals, employees and unemployed workers, (FH-DADS)¹. Most of the existing studies are using survey data, but a notable exception is Anderson and Meyer (1997). When concerned with the analysis of take-up behaviors, administrative data presents two main advantages. They are usually more reliable and larger than *ad hoc* surveys. Moreover, they include short unemployment spells (lower than a month) and make it possible to sample from inflows rather than the stock. This is all the more important to our purpose, as we are dealing with a dynamic set up where temporary non take-up is suspected. In comparison with Anderson and Meyer, our estimations are directly based on a structural model of claiming behaviors where job search behaviors are endogenous and where claiming may take time and effort. The advantage of a structural model is its ability to identify clearly, through the estimates, the economic mechanisms behind take-up. The decomposition of the participation process is crucial to provide advices to improve the effectiveness of the UI system as an insurance device (Heckman and Smith [2004]). Moreover, we are able to estimate the welfare costs of claiming frictions.

The model is presented along with stylized facts in section 2. In section 3, we discuss our dataset, the empirical specification and the estimation strategy. Section 4 presents our results.

2 A job search model with endogenous unemployment insurance take-up

The features of the French UI system and some stylized facts

We investigate the UI system ongoing in France between July 2001 and December 2002. The model mimics the main features of this system, which is largely similar to the existing systems in most of the OECD countries. The French system provides constant unemployment benefits for a limited period of time. All workers registered at the unemployment agency are helped and followed during their job search (see Crépon *et al.* [2005] for a description of the French active policy). Regular interviews with caseworkers and, for some workers, participation in training programs create non monetary costs/benefits of participation and are likely to affect job search behaviors (see Black *et al.* [2003])². Lastly, until a recent change, the sanction rate was almost null. For that reason and for sake of simplicity, we do not model sanctions.

¹FH, which stands for *Fichier Historique* are the records of the French national employment agency, while DADS, which means *Déclarations Annuelles des Données Sociales* are the French administrative linked employer-employee data.

²For example, the UI can cause a shift from informal job search methods (which cannot be observed by the employment agency) to observable methods (van den Berg and van der Klaauw [2006]).

The receipt of the unemployment compensation is not automatic. Eligibility depends on the past employment duration. Although this rule is fairly simple, it is generally unknown and the claiming process is complicated and time consuming. An unemployed worker has first to contact his local unemployment agency. He has to fill a form, describing precisely his situation and has to provide different documents to prove his entitlement rights. Eventually, he has to show up at his local agency within the first week following his claim. Hence, to make successfully a claim, a worker has to be informed, understand and follow different administrative steps.

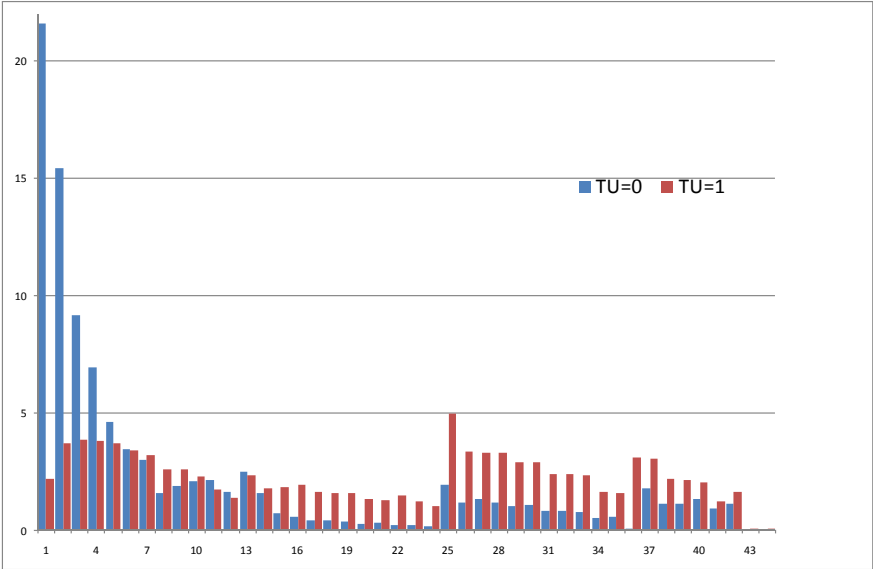


Figure 1: Distribution of unemployment duration by take-up status (in weeks). $TU = 1$ the worker receive the unemployment insurance during his unemployment spell. $TU = 0$: the worker will not receive the UI.

The analysis sample will be presented later but it is useful to provide some empirical evidence before going into the model presentation. This evidence motivates the way we model the take-up of the UI and give a preview of the potential economic mechanisms. Our sample only includes eligible male workers between 30 and 50 years of age. In this sample, the take-up rate is around 40%. By looking at the distribution of unemployment duration by take-up status (Figure 2), we see that a huge fraction of workers who do not claim unemployment benefits (labelled $TU = 0$ in the Figure 2) leave unemployment very quickly suggesting that workers with good employment prospects do

not make efforts to claim for the unemployment benefits. Nevertheless, among workers who receive unemployment benefits during their unemployment spell (labelled $TU = 1$ in Figure 2) the mean duration without receiving any compensation is about 3 months. This shows that claiming takes time and is potentially costly.

Finally, a logistic regression shows the determinants of the UI take-up probability. We replicate here the empirical estimation made in a number of existing studies on the subject, ignoring both the endogeneity of unemployment duration and the dynamic nature of the problem. Results are displayed in Table 1. The probability of receiving the unemployment compensation is positively correlated with the average monthly wage in the worker's previous job³. Since the amount of unemployment benefits is positively linked with the past wage, the incentives to claim increase with the wage. There is no clear pattern by occupation but the probability to receive UI is positively correlated with the expected UI duration. These elements suggest that the worker trades off the value of UI with existing transaction costs. Our model is designed to capture this trade-off and the stylized facts presented above.

Table 1: Probability of UI receipt among entitled workers

	Estimates	s.d.
Intercept	-4.128***	(0,171)
log(past wage)	0,410***	(0,025)
Potential compensation duration (ref.: 4-7 months)		
15 months	0,023	(0,056)
30 months	0,075*	(0,044)
Occupation (ref.: plant workers)		
Employees	0,212***	(0,043)
Technicians and associate prof.	0,097***	(0,037)
Managers and prof.	-0,119***	(0,044)

Significance at 1% level: *** ; at 10% level: *; standard errors in parenthesis.

Source: FH-DADS, 29 834 eligible non employment spells starting between 07/2001 and 12/2002.

The model

We provide a partial equilibrium job search model with infinitely lived agents. As it will be the case in our estimations, we only consider workers eligible to the unemployment insurance. Time is continuous and the labor market is at the steady state. We distinguish in our model three unemployment states, denoted by j , depending on whether the unemployed worker is in the claiming process (state N), receives the unemployment insurance (state P) or has exhausted his rights (state

³The wage is computed using the job spells in the year before the entry into unemployment

L). In each of these states j , the individual chooses a job search effort (e_j , with $j = \{N, P, L\}$) and a reservation wage (R_j). The cost of search efforts is noted $c_j(e_j)$ (with $j = \{N, P, L\}$), with $c(\cdot) > 0$, $c(0) = 0$, $c'(\cdot) \geq 0$ and $c''(\cdot) > 0$. We allow for the search technology, sum up by the job arrival rate λ_j , to be different in each state. For sake of simplicity, the wage offer distribution $F(\cdot)$ is not state dependent and the job acceptance rate thus reads $\lambda_j e_j (1 - F(R_j))$ when in state $j = \{N, P, L\}$.

We model the take-up decision as the result of an effort to deal with the claiming frictions that is the complexity of the administrative process. The claiming process is costly and takes time, the worker has to understand the administrative requirements, collect the documents needed and fill a claim. In state N , the claiming effort, noted δ , is chosen optimally and affects the duration without compensation. The cost of claiming efforts is $c_\gamma(\delta)$ and the cost function satisfies the same properties as the cost of search effort. Claiming frictions are modelled in a similar way as search frictions. An eligible worker switches from state N to P , where he receives the UI, at a rate $\gamma\delta$. γ is thus an index of the frictions in the claiming process, in the spirit of the job arrival rates. One of the aim of this paper is to get estimates of these claiming frictions together with evaluation of the welfare cost they induce.

In each state j , the individual instantaneous utility u_j is supposed to depend on his past employment wage w and we assume $u_j = u(a_j + b_j w)$. a stands for leisure or domestic production which can depend on the individual's status. We include w for two reasons. First, the unemployment benefits are calculated using past wages⁴. More generally this can be thought as a very stylized way to account for precautionary savings, that we do not model directly, or any form of dependence between past wages and unemployment value. Remark that even for workers who get an unemployment compensation (that is in state P), b_P cannot be interpreted as the replacement ratio, but more generally as a statistical link we want to estimate.

We now introduce the value functions. We denote ρ the discount rate. The value of unemployment in state N , where the worker claims for benefits and searches for a job, reads:

$$\begin{aligned} \rho V_N(w) = & u(a_N + b_N w) - c_N(e_N) - c_\gamma(\delta) + \\ & \lambda_N e_N \int_{R_N} (J(x) - V_N(w)) dF(x) + \gamma \delta \text{Max}\{V_P(w) - V_N(w), 0\} \end{aligned}$$

with $J(x)$ the value of a new job with a wage x . Job search and claiming activities are simultaneous. The worker chooses e_N and δ to maximize his intertemporal utility. The first order conditions and

⁴In France the replacement rate ranges between 57 and 75% depending on the previous wages. Since the definitions of wage is different from the total labor income, the actual replacement rates are often lower.

the indifference condition defining the reservation wage are:

$$c'_N(e_N) = \lambda_N \int_{R_N} \frac{\partial J(x)}{\partial x} \bar{F}(x) dx \quad (1)$$

$$c'_\gamma(\delta) = \gamma \text{Max}\{V_P(w) - V_N(w), 0\} \quad (2)$$

$$R_N \text{ s.t. } J(R_N) = V_N(w) \quad (3)$$

In some cases, the worker has no incentive to claim the unemployment benefits and thus his optimal claiming effort equals zero. This is especially true if the unemployment benefits are small with respect to the claiming costs or if the worker expects his search technology to deteriorate dramatically in state P ($\lambda_P \ll \lambda_N$).

In state P , the worker searches for a job with a new technology and receives benefits. We assume that the insurance ends, at each period, with a probability μ . In the actual UI system, the insurance duration is not stochastic. However, this assumption simplifies the model and can be seen as an appropriate simplification for two reasons. First, the fact that the worker can gain the right to benefits extension if he works a little during his unemployment period (a system called '*activité réduite*', reduced activity) introduced some form of uncertainty. Moreover, the model and the empirical investigation are mainly focused on the transitions between state N and P and not on the exit rate profiles when the worker is in state P . What is thus crucial is to get the expectation of the value of unemployment in this state right but not necessary to fit perfectly the exact exit rate profiles in this state. Even if we agree that this is an imperfect assumption, we think that the gain in term of computational time is sufficiently significant to justify it. If the end of the unemployment insurance is taken as deterministic, the search intensity and reservation wage become functions of the time spend in state P . This is perfectly feasible. However the estimation of the model requires to solve it for each guess on the structural parameters and for each combination of the state variables (w , any other form of heterogeneity and the time spends in unemployment if it is a state variable). The estimation of the deterministic model is very cumbersome in practice. The use of a stochastic framework reduces the dimension of the problem. This allow us to introduce unobserved heterogeneity (see in the next section). For each worker, μ will be chosen in the estimation such that $1/\mu$ (the expected benefits duration) matches the 'true' benefits duration at the entry in state P .

The value of unemployment in states P reads

$$\begin{aligned} \rho V_P(w) &= u(a_P + b_P w) - c_P(e_P) \\ &+ \lambda_P e_P \int_{R_P} (J(x) - V_P(w)) dF(x) + \mu(V_L(w) - V_P(w)) \end{aligned}$$

The optimal search intensity and reservation wage satisfy:

$$c'_P(e_P) = \lambda_P \int_{R_P} \frac{\partial J(x)}{\partial x} \bar{F}(x) dx \quad (4)$$

$$R_P \text{ s.t. } J(R_P) = V_P(w) \quad (5)$$

The higher the duration of the insurance (that is the lower μ), the higher the reservation wage and thus the lower the search intensity. Besides, as usual, the level of the insurance reduces the search effort. In the last state, L , the worker is still looking for a job but no longer receives the unemployment compensation. The value of unemployment reads:

$$\rho V_L(w) = u(a_L + b_L w) - c_L(e_L) + \lambda_L e_L \int_{R_L} J(x) - V_L(w) dF(x)$$

Eventually, for the sake of clarity, the definition of the value of employment $J(x)$ is postponed to the empirical specification.

2.1 How claiming and job search react to a change in the UI system?

What are the effects of a change in the UI design, especially a change in the replacement rate or in the insurance duration? In our framework, they are not standard since the effort devoted in claiming the UI and searching for a job interact. Consider again equations (1), (2) and (3). Reservation wage depends on the value of unemployment in state N which is affected by the claiming frictions, the generosity of the unemployment insurance but also by the relative efficiency of job search in state N and P (λ_N vs λ_P).

First, under simple conditions⁵, a rise in b_P increases the value of unemployment in both N and P states and thus the reservation wage, R_N . In this case, the exit rate from unemployment decreases in state N . The worker postpones his job search to state P and increases his claiming effort since the unemployment insurance is more profitable. A decrease in the claiming friction (a rise in parameter γ) or an improvement in the efficiency of job search in state P have the

⁵We abstract from the eligibility effect (Mortensen, 1977). A rise in the value of insured unemployment increases the value of employment and, in some cases, may decrease the reservation wage.

same effects. From these simple example, it becomes obvious that the take-up and the job search behaviors interact. Estimation of the take-up behaviors requires a model encompassing both. This paper provides such a model.

3 Empirical Application and Estimation Method

We begin this section by presenting the data and the selected sample, then we discuss the estimation methods.

3.1 The data

The FH-DADS data⁶ are similar to the data used by Anderson and Meyer (1997). This is a match of the yearly declarations of social data (*DADS*), where employers of the private and semi-public sectors report earnings, hours and job duration of individuals they have employed during the year, together with data from the insurance system. The original datasets are 1/24 nationally representative samples⁷. The merge of these datasets includes any individual who appears in one or another of these records between January 1st, 1999 and December 31st, 2004. A worker can thus be included even if he did not experience any unemployment spell or, on the contrary, did not experience any employment spell. The data are longitudinal and give information on the private and semi-public sector back to 1976, on registered unemployment history back to 1993 and on insured unemployment back to 1999.

The administrative nature of these data make them attractive for a study of non take-up. They provide information on a daily basis and allow us to work on outflows from employment. We thus observe all unemployment spells, even those of short duration. In addition, work history can be traced back to 1976, and individuals are followed even when they move geographically (within France). For each job in the private or semi-public sectors, we observe the start and end dates, earnings and number of hours worked (after 1993). These information are used to predict eligibility and to calculate the reference wage which determines the amount of benefits. Moreover, we observe all insured unemployment spells the individual had between 1999 and 2004. As a result, we are able to determine eligibility at the time of job separation and the take-up decision and timing.

The main drawback of this dataset, which is common to most of the dataset which only cover the private sector, is that missing days in the employer-employee data do not necessary mean that the individual was unemployed. Four main reasons may explain why an individual does not appear

⁶These data are available since June 2009 and are managed by the research and statistics department of the french ministry of social affairs (DARES).

⁷Workers born on October of an even-numbered year are sampled.

in the FH-DADS dataset for a given period: he may be unemployed but not taking up UI, out of the labour force, employed but not by an entity that is subject to the mandatory report, or misidentified⁸. As a result, an individual who is observed neither in the DADS, nor in the records of the national employment agency is not necessarily an unemployed worker who does not take up unemployment insurance. Whether the individual is unemployed or inactive is however not relevant to our purpose as long as we restrict our analysis to the entitled workers: if the individual exits the labour force although he is entitled to compensation, he still forgoes money. Moreover, maternity and sickness leaves do not generate an exit from employment in the DADS dataset, so the inactivity periods we might worry about are essentially due to schooling, early and regular retirement and entry into programmes of the social security system other than unemployment. We circumvent these problem by considering in our analysis sample only *male* workers between 30 and 50 years of age.

The fact that some jobs (public jobs and self-employment) are not reported in the DADS sample is, on the contrary, more problematic. However, using the French LFS, we can see that the transitions from the private and semi-public sectors to of these jobs jobs not reported in the DADS are limited. Finally, another limitation of the DADS data is that we do not know the reason why the job ended. Nevertheless, workers who quit voluntarily are still eligible for benefits but after four months of unemployment. We do not see any spike at four months in the data. Besides, a worker who voluntary quits is likely to quit his current job to another (more attractive) job. For that reason we exclude very short unemployment spell (less than a week).

3.2 The sample

The analysis sample includes male between 30 and 50 having a non employment spells starting between July 2001 and December 2002⁹. For most of the workers, the eligibility depends on the number of days worked in the past 18 months (see Table 7 in Appendix). All workers in our sample satisfy the eligibility criteria. We exclude workers who were employed in sector with different eligibility rules¹⁰. We may thus exclude some workers who are eligible, but we are reasonably sure about the eligibility of the workers in our sample. For all spells, we build a 24 months observation window, the spell being censored after 24 months. As mentionned before, we only consider unemployment spell above 7 days. Table 8 in Appendix describes the composition of the sample.

⁸Errors in the identification of individuals concern about 5% of the original sample.

⁹Between July 2001 and December 2002 the design of the unemployment insurance system has remained unchanged.

¹⁰Especially, we drop workers from the so-called semi-private sector (this accounts for 6,3% of the outflows from employment in 2001 and 2002). See the details of our sample selection in Appendix.

Table 2 shows the take-up rates in our sample, unconditional and conditional on the time spent out of unemployment. The observed take-up rates are around 30%, a result comparable to the one obtained by Anderson and Meyer [1997] on their sample of outflows from employment. Observed take-up rates clearly increase with the time spent out of unemployment.

Table 2: Take-up rates unconditional and conditional on duration out of employment

	All	Unskilled	Skilled	
Unconditional	%	31.65	31.26	32.33
	N	5712	3600	2112
Total unemployment duration				
>4 weeks	%	35.6	34.79	37.07
	N	5672	3570	2102
>12 weeks	%	43.15	42.56	44.19
	N	5324	3366	1958
> 26 weeks	%	47.71	47.56	47.97
	N	4734	3006	1728
> 39 weeks	%	48.72	48.56	49
	N	4288	2715	1573
> 52 weeks	%	50.37	50.5	50.15
	N	3971	2505	1466

This runs along with the differences in unemployment duration between those who take up and those who do not displayed in Figure 2 . hence, the duration to registration is likely to be non randomly right-censored. Before going to the estimation of our structural model, we estimate a competing risks model with unobserved heterogeneity to account for the endogenous censoring and to serve as guidelines for our empirical specification. Such a model is implicitly very similar to the model presented above. Its results are likely to be more informative about the main features of the data than the logit regression presented in Section 2. The details of the model are presented in Appendix and results are displayed in Table 3.

Endogenous censoring affects only marginally the link between the reference wage and the exit rate to registration. Higher reference wages positively affect both the exit rate to registration and the exit rate from employment. Covered work experience no longer significant has a positive effect on the return to employment but, perhaps surprisingly, negative on the receipt of unemployment insurance. Individuals with stable employment trajectory are likely to find a job quickly. In that case, their claiming effort is lower although they are entitled to longer unemployment benefits duration. The coefficients of the distribution of unobserved heterogeneity imply that there exists a negative correlation between the log of risk-specific unobserved components. Individuals who are

	Employment risk		Compensation risk	
high skilled	-0,13	***	-0,05	***
	0,019		0,023	
log(reference wage)	0,11	***	0,09	***
	0,017		0,020	
previous covered experience (ref: 4 to 6 months)				
6 to 12 months	0,51	***	-0,80	***
	0,044		0,029	
more than 12 months	0,69	***	-1,26	***
	0,038		0,022	
baseline hazard (weeks)				
0-2	-4,67	***	-1,79	***
	1,429		0,142	
2-4	-4,33	***	-3,29	***
	1,429		0,145	
4-8	-4,39	***	-3,75	***
	1,430		0,144	
8-16	-4,77	***	-4,23	***
	1,431		0,144	
16-30	-5,31	***	-4,91	***
	1,432		0,146	
30-52	-5,54	***	-5,16	***
	1,432		0,147	
>52	-6,74	***	-5,89	***
	1,434		0,147	
unobserved heterogeneity				
nu_1	0,00		0,00	
nu_2	-0,08		0,00	
	1,453		0,081	
probabilities				
Pbb	0,00			
Pbh	0,01			
Phb	0,53			
Phh	0,46			

Table 3: Competing risks model

Table 4: Moments on the analysis sample

Censoring in N	7.0%
Share of workers making N → P	26.0%
Share of workers making N → J	66.8%
Share of workers making N → J (within 3 months)	55.7%
Average duration in N given N → P	2.0 months
Average duration in N	4.7 months

more likely to register are less likely to find a job quickly¹¹. Our model is especially designed to account for such a selection process.

For the preliminary results reported here, data are transformed to monthly data and we select only skilled workers (> high school). We end up with 7481 observations. Moments on the analysis sample are reported in Table 4. These moments will be used latter to check our ability to replicate the main features of the data.

On this estimation sample, the take-up rate is 26.0% and two-third of the sample makes a direct transition between uninsured unemployment (state N) and employment, most of them within three months. For those we receive the UI, the average duration without insurance is about 2 months which is a sign of significant claiming frictions. The estimation of our structural model will provide estimations of these frictions.

3.3 Empirical specification.

In order to estimate our model, we need to specify functionnal forms for the utility functions, job offer distribution and arrival rates. Remember that, for each possible combination of observed and unobserved variables, we need to solve our model to find the optimal search efforts, the claiming effort and the reservation wages. These values are needed to compute the contribution of the individuals to the likelihood. Generally speaking, the empirical specification must balance between a framework that must be rich enough and computational limits¹².

For an individual i , the utility function reads $u_{ij}(w_i) = \log(a_j + b_j \ln w_i)$, with w the monthly wage corresponding to the last employment spell. The discount rate ρ is set to .005. We solve the model on a discrete wage grid (100 points). When a wage does not equal any point on the grid,

¹¹Given our specification, the covariance between $\log(\nu_R)$ and $\log(\nu_J)$ is $\frac{a_J \sigma_{w_1}^2 + b_J \sigma_{w_2}^2}{\sqrt{(a_J^2 \sigma_{w_1}^2 + b_J^2 \sigma_{w_2}^2)(\sigma_{w_1}^2 + \sigma_{w_2}^2)}}$ (Kamionka *et al.* [2001]).

¹²The estimations are programmed in Fortran 90 but run on a desktop computer located in the DARES (ministry of social affairs). This computer has not been especially chosen for intensive computational tasks.

we use interpolation to obtain worker's optimal efforts. Data may exhibit a positive correlation between the exit rate from unemployment and the past wage. Unobserved heterogeneity is also essential to understand the selection into the UI. To be able to mimic these aspects, we assume that the arrival rates are:

$$\begin{aligned}\lambda_{iN} &= \exp(m_{0N} + m_{1N} \ln w_i + \nu_i) \\ \gamma_i &= \exp(m_{0\gamma} + m_{1\gamma} \ln w_i + c_\gamma \nu_i) \\ \lambda_{iP} &= \exp(m_{0P} + m_{1P} \ln w_i + c_P \nu_i)\end{aligned}$$

where ν_i , an unobserved random effect, is normally distributed $N(0, \sigma_\nu)$. In this version of the estimation, we fix the m_{1s} parameters to zero. We assume that job offers are drawn in a shifted log-normal

$$F_{\text{Offers}}(w) = F_{\text{Normal}}\left(\frac{\ln w - \ln w_{\text{inf}} - \mu_F}{\sigma_F}\right)$$

The lower bound w_{inf} is set to 300 euro . Finally, we need to characterize the value of employment J for a worker coming from unemployment and paid at a wage w_{new} .

$$\rho J(w_{\text{new}}) = w_{\text{new}} + q (\mathbb{E}[\text{value of unemployment}] - J(w_{\text{new}})) + \lambda_J \int_w (J(x) - J(w_{\text{new}})) dF(x)$$

where q stands for the job destruction rate, λ_J for the job-to-job arrival rate which is assumed exogenous. Depending on the assumptions on J , the model can be relatively straightforward or very complicated to solve. In this version of the paper, we add the following assumptions:

- there is no job-to-job mobility ($\lambda_J = 0$) (this is not a crucial assumption, it will be relaxed in a future version);
- the job destruction rate is set to $q = .003$ to match the average employment duration in the data;
- the expectation in state J about the value of employment corresponds to what the worker just experienced (V_N or V_P depending on where the worker comes from). This is a key assumption because it simplifies the expression for the reservation wage and thus speeds up dramatically the computations.
- there is no limit to the duration of the unemployment compensation ($\mu = 0$) and thus we

discard state L. We do not record transitions from state P to state L and assume the worker stays in P (this is not a crucial assumption, it is made to get benchmark estimation and will be relaxed thereafter in a future version).

3.4 Maximum likelihood estimation

We follow individuals from their transition from employment into non-registered unemployment until their transition to employment if any. For each worker, we observe his unemployment history that is his transitions between the unemployment states and the durations D_{ij} in months in each state. If the worker finds a job, we also observe his reemployment wage.

As an example, consider an eligible worker i . Assume that he begins in state N , moves to P after D_{iN} periods and finds a job with a wage w_i^r after D_{iP} periods in this state. His contribution to the likelihood amounts to:

$$\begin{aligned} \ell_i(D_{iN}, D_{iP}, D_{iL} = 0, w_i | \theta, w_i^p, t_i, X_{io}) &= \exp(-(\lambda_{iN} e_{iN}^* \bar{F}(R_{iN}^*) + \gamma_i \delta_i^*) D_{iN}) \times \gamma_i \delta_i^* \\ &\times \exp(-(\lambda_{iP} e_{iP}^* \bar{F}(R_{iP}^*) + \mu_i) D_{iP}) \times \lambda_{iP} e_{iP}^* \times f(w_i) \end{aligned}$$

Then this contribution must be integrated with respect to the unobserved heterogeneity parameter ν which affects the λ s and γ . The other contributions are similar and easily derived from the model (see in Appendix). Recall that the optimal values depend on the structural parameters and the worker's characteristics. Identification of these parameters rely on the observed duration and reemployment wages. One of the usual difficulty of this type of models comes from the fact that, for some individuals, we may predict reservation wages above the observed reemployment wages. To deal with this problem, we assume that log-wages are observed with an error which is i.i.d across job spells and individuals and is distributed according to a log-normal distribution with mean 1 and variance σ_ϵ . To reduce the set of parameters to estimate in this preliminary attempt, σ_ϵ is set to one but will be estimated in the next version of the paper.

4 Results

Before commenting the parameters' value (reported in Table 6), it is useful to check the ability of our model given these estimates to fit the basic features of the data. For that purpose, we run simulations with the same observation window (18 months) and workers' characteristics (same distribution of past wage). Results are displayed in Table 5. The unemployment-to-job transition moments are reasonably well fitted: both the share of workers and the duration are matched.

	Real data	Sim. data ¹³
Share of workers making $N \rightarrow J$	66.8%	61.7%
Share of workers making $N \rightarrow J$ (within 3 months)	55.7%	54.2%
Average duration in N given $N \rightarrow P$	2.0	2.5
Average duration in N	4.7	3.9
Censoring in N	7.0%	1.7%
Share of workers making $N \rightarrow P$	26.0%	36.5%

Table 5: Comparison of the moments on the analysis sample and the same moments on simulated data

However, our model do not generate enough censoring in state N . The main reason is obvious if one looks at the last moments (share of workers switching from state N to state P). The model tends to over-estimate the take-up rate. The claiming frictions are thus underestimated. We will return to that point later and now consider the estimated parameters' value.

Results are reported in Table 6. We first look at the parameters relating the instantaneous utility in unemployment and the worker's past wage. The constants are almost null and that the "replacement rates" are ranked as expected ($b_N < b_P$). Notice that b_P is low when compared with the actual UI rules. Indeed, the replacement rates are supposed to be around 60% on the paper. However, the wage used to determine the unemployment benefits is not the exact previous wage since it excludes some form of compensation. The "real" replacement rate can thus be lower than the official replacement rate (which is a well known fact). Moreover, the value in term of utility of the unemployment compensation might be lower than its monetary value.

The instantaneous utility is higher in state P (because of the receipt of UI). This does mean that the intertemporal utility is necessary higher since the different unemployment states correspond to different job search technology. We can first compare the relative efficiency of the search technologies by looking at λ_N and λ_P for the median individual ($\nu_i = 0$): $\lambda_N = 2.80$ and $\lambda_P = 0.66$. There is a clear loss in term of job search efficiency between state N , where the worker does not receive any compensation, and state P , where he is registered at the unemployment insurance. This, together with higher unemployment income, divide the exit rate from unemployment by more than two both because the worker decreases his search intensity and increases his reservation wage (see Figure 2 which displays the exit rate from unemployment in both state).

Given that the cost functions are identical, they can also directly compared γ , the index of the claiming frictions, with the λ s. For the median worker, $\nu_i = 0$, $\gamma = 1.39$. The claiming frictions are thus substantial. If the worker spends on units of search effort and one unit of claiming effort

	Est.	s.d.
a_N	1.35	(.0050)
a_P	0.00	(.0001)
b_N	0.17	(.0091)
b_P	0.27	(.0072)
μ_F	6.16	(.0049)
σ_F	0.43	(.0007)
σ_ν	7.20	(.0019)
c_P	-0.62	(.0002)
c_γ	0.44	(.0000)
m_N	1.03	(.0002)
m_P	-0.41	(.0000)
m_γ	0.33	(.0001)

Table 6: Parameters' estimates

(for the same cost in term of utility since the cost functions are identical), his job arrival rate in state N amounts to 2.80 while he switches to state P at a rate 1.39. The claiming frictions are thus twice higher.

As mentioned before, we over-predict the take-up rate and thus probably underestimate the claiming frictions. Which feature of the model may drive this problem. Figure 2 displays the estimated exit rates ($e_N \lambda_N \bar{F}(R_N)$, $e_P \lambda_P \bar{F}(R_P)$ and $\gamma \delta$) as a function of the past wage. The level of one curve with respect to the others reflects our estimations of the job arrival rates and claiming friction parameter. Notice that the unemployment-to-job exit rate is a decreasing function of the past wage. This comes from the positive relationship between the instantaneous utilities (and thus values of unemployment) and this wage. Unfortunately, the negative correlation of the unemployment exit rate and past wage is not confirmed on real data. The estimation of a competitive risk model (see above) shows the opposite correlation. High wage workers are also more efficient in job search or unemployment insurance claiming. Our model could reproduce the right correlation if we allow the λ s and γ to depend on w . The estimation presented here assume $m_{1j} = 0$. We thus need to relax this hypothesis. Nonetheless, in comparison with the estimated search frictions, our estimation of the claiming frictions are already striking and show how significant they can be.

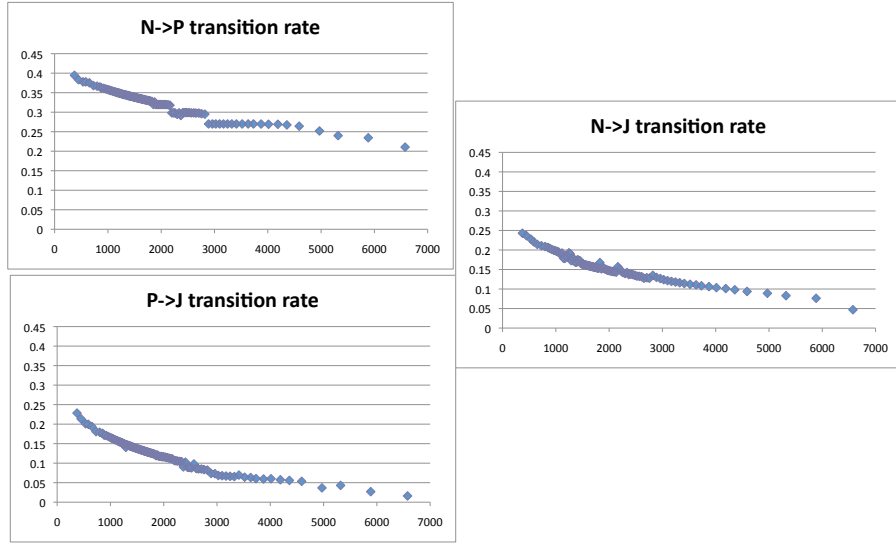


Figure 2: Exit rate profiles as a function of past wages (simulated data)

5 Conclusion

This paper provides a model that incorporates take-up of the unemployment insurance in a job search framework. The worker faces claiming frictions and the receipt of UI takes time and effort. The model provides a simple way to model selection into participation and sheds new light on the link between the job search and the claiming efforts. It is estimated using a unique administrative database providing detailed informations about the worker’s labor market history and claiming behaviors. We show that claiming frictions are substantial and higher than job search frictions.

In this version of the paper, some assumptions have been made that needed to be relaxed. Especially, the arrival rates should be a function of the past wage and we need to account for the heterogeneity in the entitled UI durations. The aim of this paper is also to provide conterfactual experiments to assess precisely the welfare cost of the claiming frictions: this can be done be comparing the welfare levels given our estimates and a situation where there isn’t such frictions, that is where the workers switch immediately between N and P ($\gamma \rightarrow \infty$).

6 Appendix

The eligibility rules. Table 7 displays the UI duration as a function for the number of months worked in the past months.

Covered work experience	Age	Maximal length of compensation
4 months in the past 18 months	-	4 months
6 months in the past 12 months	-	7 months
8 months in the past 12 months	< 50 years old	15 months
	\geq 50 years old	21 months
14 months in the past 24 months	< 50 years old	30 months
	\geq 50 years old	45 months
27 months in the past 36 months	between 50 and 54 years old	45 months
	\geq 54 years old	60 months

Source: Unedic

Table 7: Potential benefit duration (January 2001 - December 2002)

Table 8: Sample Composition

	All	Skilled	Unskilled
N	18048	6533	11515
Share of skilled workers	36.20		
Occupation in previous job			
artisans and sellers	2.12	5.86	
white collar	14.95	41.30	
intermediary	19.13	52.84	
employees	10.83		16.98
workers	52.97		83.02
Age in 2001			
31	14.75	14.57	14.85
33	13.62	13.35	13.78
35	12.52	12.60	12.48
37	12.44	11.83	12.78
39	10.78	10.49	10.95
41	8.87	9.46	8.54
43	7.76	8.11	7.56
45	6.17	6.72	5.86
47	6.83	6.77	6.86
49	6.26	6.11	6.34
Maximal compensation duration			
4 months	4.73	2.10	6.23
7 months	3.28	1.47	4.31
15 months	6.29	3.63	7.80
30 months	85.70	92.81	81.67

A competing risks model. We estimate a competing risks model with unobserved heterogeneity. Formally, let T_J and T_R be two competing latent duration processes representing the durations spent in unregistered non employment until reemployment and the completion of the claiming process, respectively. Given the risk-specific observed and unobserved characteristics, T_J and T_R are assumed independent: $T_J | X_J, \nu_J \perp T_R | X_R, \nu_R$.

Let C be the censoring process. We observe $\min\{T_J, T_R, C\}$. T_R is censored in two circumstances: if the worker exits to employment before his potential claim succeeds, or is still unemployed and unregistered one year after job separation¹⁴. In a mixed proportional hazard framework (Lancaster [1999], van den Berg [2001]), the likelihood function writes:

¹⁴This second type of censoring derives from entitlement rule which require that the individual must claim within a year).

$$L(t_J, t_R | X_J, X_R; \Theta) = \prod_{i=1}^N \int_{-\infty}^{+\infty} \ell(t_J, t_R | X_J, X_R; \Theta) g(\nu) d\nu$$

where $\ell(t_J, t_R | X_J, X_R; \Theta)$ is the individual contribution to the likelihood,

$$\begin{aligned} \ell(t_J, t_R | X_J, X_R; \Theta) &= \left(h_J^{(0)}(t_J) \exp(X_J \beta_J + \nu_J) \right)^{\delta_J} \left(h_R^{(0)}(t_R) \exp(X_R \beta_R + \nu_R) \right)^{\delta_R} \\ &\quad \times \exp \left(- \sum_{k=J,R} \exp(X_k \beta_k + \nu_k) \int_0^t h_k^{(0)}(s) ds \right) \end{aligned}$$

with Θ the set of parameters to be estimated, (X_k, ν_k) the observed and unobserved attributes, $h_k^{(0)}(\cdot)$ the k -specific baseline hazard ($k = J, R$), δ_k risk-specific censoring dummy and $g(\cdot)$ the joint distribution of the ν_k s. The results reported in Table ?? derives from the estimations of models parametrically specified, with Weibull-type baseline hazards. We retain a discrete distribution for the unobserved heterogeneity. We take a two factor loading specification: $\nu_k = \exp(a_k w_1 + b_k w_2)$ with w_1 and w_2 two independent discrete random variables such that $w_1 \in \{0, w_1^b\}$ and $w_2 \in \{0, w_2^b\}$. For identification, we set $a_R = b_R = 1$. The parameters to be estimated then are a_J, b_J, w_1^b, w_2^b and the probabilities of the distribution, P_m with $m = 1, \dots, 4$.

References

- Adda J. and Cooper R.** [2002], *Dynamic Economics*, The MIT Press.
- Aizer A. and Currie J.** [2004], “Networks or Neighborhoods? Correlations in the Use of Publicly-Funded Maternity Care in California”, *Journal of Public Economics*, 88(12), 2573-2585.
- Anderson P. M. and Meyer B. D.** [1997], “Unemployment Insurance Take-up Rate and the After-Tax Value of Benefits”, *Quarterly Journal of Economics*, 112(3), 913-937.
- Black D., Smith J., Berger M. and Noel B.** [2003], “Is the Threat of Reemployment Services More Effective than the Services Themselves? Evidence from Random Assignment in the UI System”, *American Economic Review* 93(4): 1313-1327.
- Van den Berg G.J.** [2001], “Duration models : specification, identification and multiple durations”, in Heckman J. and E. Leamer (eds.), *Handbook of Econometrics Vol.5*.
- Van den Berg G.J. and Eckstein Z.** [2003], “Empirical Labor Search: a survey”, *IZA Working Paper n°929*.
- Van den Berg G.J. and van der Klaauw B.** [2006], “Counseling and Monitoring of Unemployed Workers: Theory and Evidence from a Controlled Social Experiment”, *International Economic Review*, 47, 895-936.
- Bertrand M., Luttmer E. and Mullainathan S.** [2000], “Network Effects and Welfare Cultures”, *Quarterly Journal of Economics*, 115(3), pp. 1019-1055.
- Blank R. M. and Card D. E.** [1991], “Recent Trends in Insured and Uninsured Unemployment: Is There an Explanation”, *Quarterly Journal of Economics*, 106(4), 1157-1189.
- Clark A.E.** [2003], “Unemployment as a social norm: psychological evidence from panel data”, *Journal of Labor Economics*, 21(2), 289-322.
- Currie J.** [2006], “The Take-up of Social Benefits”, forthcoming in Auerbach A., Card D. and J. Quigley (eds.), *Poverty, the Distribution of Income, and Public Policy*, (New York: Russell Sage).
- Duclos J.-Y.** [1995], “Modeling the Take-Up of State Support”, *Journal of Public Economics*, 58, 391-415.
- Gorter C. and Kalb G.R.J.** [1996], “Estimating the Effect of Counseling and Monitoring the Unemployed Using a Job Search Model” *The Journal of Human Resources*, Vol. 31, No. 3, pp. 590-610.
- Heckman J. and Smith J.** [2004], “The Determinants of Participation in a Social Program: Evidence from a Prototypical Job Training Program”, *Journal of Labor Economics* 22(4): 243-298.

- Hernandez M. and Pudney S.** [2007], “Measurement error in models of welfare participation”, *Journal of Public Economics*, 91(1-2), 327-341.
- Hernanz V., Malherbet F. and Pellizari M.** [2004], “Take-up of Welfare Benefits in OCDE Countries: A Review of the Evidence”, *OCDE*.
- Hopenhayn H. and Nicolini J. P.** [1997], “Optimal Unemployment Insurance”, *Journal of Political Economy*, 105 (2), 412-438.
- Lancaster T.** [1990], *The econometric analysis of transition data*, Cambridge University Press.
- McCall B.** [1995], “The Impact of Unemployment Insurance Benefit Levels on Reciprocity”, *Journal of Business and Economics Statistics*, 13(2).
- McVicar D.** [2008], “Job search monitoring intensity, unemployment exit and job entry: Quasi-experimental evidence from the UK”, *Labour Economics*, Vol. 15, No. 6, pp. 1451-1468.
- Moffit R.** [1983], “An Economic Model of Welfare Stigma”, *American Economic Review*, 73(3), 1023-1035.
- Shavell S. and Weiss L.** [1979], “Optimal Payment of Unemployment-Insurance Benefits over Time”, *Journal of Political Economy*, 87 (6), 1347-1362.
- Shimer R. and Werning I.** [2006], “On the Optimal Timing of Benefits with Heterogeneous Workers and Human Capital Depreciation”, *Working Paper*.
- Storer P. and Van Audenrode M. A.** [1995], “Unemployment insurance take-up rates in Canada, determinants and implication”, *Canadian Journal of Economics*, 28(4), 822-835.