A Structural Model of the Unemployment Insurance Take-up

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July 2009 - IN PROGRESS

Abstract
This paper provides a structural model to explain the empirical evidences of unemployment insurance non take-up. Our framework is designed to estimate the relative importance of four determinants of the take-up decision: the expected benefit level, the imperfect information on the eligibility rules, the practical difficulties to make a claim and the non-monetary incentives such as the effectiveness of the unemployment agency as a search method. Our structural model accounts for the endogenous link between job search and benefits claiming and provides a simple way to model selection into participation. We estimate it using the French Labor Force Survey. The advantage of our model is its ability to identify clearly, through the estimates, the economic mechanisms behind the take-up.

Keywords: Unemployment Insurance Take-up, Job Search
JEL Classification numbers: J64, J65, C41

1 Introduction
Unemployment insurance (UI hereafter) has been designed to insure workers against the loss of income. However, like for all welfare benefits (Currie [2006], Hernanz et al. [2004]), the take-up among eligibles is far from 100%. In the US, the estimated take-up is around 70% depending on the state and the year (Blank and Card [1991], Anderson and Meyer [1997], McCall [1995]) and the estimations for the UK or Canada lie between 60% and 80% (Storer and Van Audenrode [1995], DWP [2008]). Theoretical studies and empirical evaluations of the UI system usually ignore these empirical evidences 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 adress this issue.

It build on the existing welfare benefits take-up literature (see Moffit [1983] and Currie [2006] for a recent survey). In our framework, the take-up is the result of a utility-maximizing decision which accounts for the gains of participating to the UI system (the expected unemployment compensation or the job search assistance) and the expected costs which depends on the practical difficulties to make a claim, which are modeled as frictions in the claiming process. We also include the possibility of an imperfect information about the eligibility rules.
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 un-
employment benefits because they leave unemployment too quickly. If a worker expects a relatively
low unemployment duration, it 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 to measure the impact of
a low take-up rate. 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 thus provide a dynamic framework in which we model both the worker’s job search and
his effort to collect informations to file for the 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 only the share of the eligible population who receives the unemployment insurance. Inter-
estingly, our model exhibits selection in the UI participation 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
of our model using data from the French Labor Force Survey. 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 political advice to improve the
effectiveness of the UI system as an insurance device (Heckman and Smith [2004]). For instance, if
non take-up is due to the complexity of the claiming process, there is an inefficiency in the design
of the system which can be corrected for.

The model is presented in section 2. In section 3, we shed lights on the economic mechanisms
behind the take-up decision. Section 4 is devoted to the data set and the empirical strategy. Section
5 presents our results. We discuss our results and conclude in section 6.

2 A model of unemployment insurance take-up

The features of the French UI system

We investigate the UI system ongoing in France between 2003 and 2006. The model mimics the main
features of this system, which is largely similar to the existing systems in most of OECD countries.
The French system, named Plan d’Aide au Retour à l’Emploi (PARE hereafter), 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 of participation and affect the job search (Black et
al. [2003])1. Since uninsured unemployed workers receive a more limited support, recipients and

1For 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]).
non recipients do not benefit from the same job search technologies. Last, until a recent change, the sanction rate was almost null. For that reason and for sake of simplicity, we do not model sanctions.

The receipt of the unemployment compensation is not automatic. The 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. The 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.

The model

We provide a partial equilibrium search model with infinitely lived agents. Time is discrete and the labor market is at the steady state. We distinguish in our structural model three unemployment states depending on whether the unemployed worker is in the claiming process (state $N$), receives an unemployment compensation (state $P$) or has exhausted his rights (state $L$). In each of these states, the individual $i$ chooses a job search effort ($e_{ij}$, with $j = \{N, P, L\}$) and a reservation wage ($R_{ij}$). In the same way, in the first step, the claiming effort, noted $\delta_i$, is chosen optimally and affects the duration without compensation. The cost of search efforts is noted $c_j(e_{ij})$ (with $j = \{N, P, L\}$) and the cost of claiming efforts $c_\gamma(\delta_i)$. In each case, $c(.) > 0$, $c(0) = 0$, $c'(.) > 0$ and $c''(.) > 0$.

Notice that the search technology can be different in each state. We thus allow the job arrival rates $\lambda_{ij}$ to differ. However, for sake of simplicity, the wage offer distribution $F(\cdot)$ is assumed to be the same. At each period, the probability to receive and accept a job offer equals $\lambda_{ij} e_{ij} (1 - F(R_{ij}))$. In state $N$, the worker makes en effort to receive unemployment benefits but face a number of frictions. 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 our framework, an eligible worker has at each period a probability $\gamma_i \delta_i$ to complete the process and receive benefits (he enters in state $P$). $\gamma_i$ is an index of the frictions in the claiming process, in the spirit of the job arrival rates of the search models.

Moreover, we account for the possibility of incomplete information about the eligibility status. If $\gamma_i \delta_i$ is indeed the true probability to complete the claim and receive the unemployment compensation, we assume that the worker is uncertain about his eligibility. This uncertainty is modeled as follows: worker with an employment duration $t_i$ in the last employment spell (whatever the number of jobs) expects to be eligible with a probability $P(t_i) \in [0, 1]$, with $P(0) = 0$. In most of the actual UI system and especially in the French system we consider, eligibility hinges on employment duration. We aim at estimating this function and at comparing the estimates with the actual rules in order to evaluate the existence of informational problems.

In each state, the individual $i$’s instantaneous utility $u$ is supposed to depend on his previous job wage: $u = u(a_{ij} + b_{ij} w_i)$, with $w_i$ his last wage. The unemployment benefits are indeed often calculated using past wages\(^2\), but more generally this can be thought as a very stilized way to

\(^2\)In France the replacement rate ranges between 57 and 75% depending on the previous wages.
account for precautionary savings that we do not model directly. Hence, even for workers who get an unemployment compensation, $b$ is not directly the replacement ratio, but represent a statistical link we want to estimate. On the top of that, $a$ stands for the preference for leisure or domestic production which can depend on the individual’s status.

We now introduce the value functions. Notice that the different transition probabilities (unemployment to job, non-insured to insured etc...) are mutually exclusive. We denote $\beta$ the discount rate and consider an unemployed $i$. The value of unemployment is state $N$ reads:

\[
V_{iN}(t_i, w_i) = u(a_{iN} + b_{iN} w_i) - c_N(e_{iN}) - c_\gamma(\delta_i) + \beta \lambda_i e_{iN} \int \max\{J_i(0, x), V_{iN}(t_i, w_i)\} dF(x) + \beta \gamma_i \delta_i P(t_i) \max\{V_{iP}(w_i), V_{iN}(0, w_i)\} + \beta (1 - \lambda_i e_{iN} - \gamma_i \delta_i) V_{iN}(t_i, w_i)
\]

with $J_i(0, x)$ the value of a new job with a wage $x$. The first argument of $J$ accounts for the elapsed employment duration which at the time of reemployment is zero. Recall that the worker in state $N$ thinks that he is not eligible with a probability $1 - P(t_i)$ which is equivalent to a worker with a zero employment duration. The first order condition on the claiming effort is simply:

\[
c_\gamma'(\delta_i(t_i, w_i)^*) = \beta \gamma_i \max\{P(t) (V_{iP}(w_i) - V_{iN}(t_i, w_i)) + (1 - P(t_i)) (V_{iN}(0, w_i) - V_{iN}(t_i, w_i))\}
\]

It is worth noting that, in some cases, the worker has no incentive to claim the unemployment compensation and his optimal claiming effort equals zero. In state $P$, the worker search for a job with another search technology and receives benefits. We assume that the insurance ends, at each period, with a probability $\mu_i$. In the actual UI system, the insurance duration is not stochastic. However, this assumption simplifies the analysis - it implies that the optimal search strategy is constant in state $P^3$. The value of unemployment in states $P$ reads

\[
V_{iP}(w_i) = u(a_{iP} + b_{iP} w_i) - c_P(e_{iP}) + \beta \lambda_i e_{iP} \int \max\{J_i(0, x), V_{iP}(w_i)\} dF(x) + \mu_i V_{iL}(w_i) + \beta (1 - \lambda_i e_{iP} - \mu_i) V_{iP}(w_i)
\]

In the last state, he is still looking for a job but no longer receives the unemployment compensation. The value of unemployment satisfies

\[\text{footnote 4: It also a way to introduce uncertainty about the insurance duration.}\]
\[ V_{iL}(w_i) = u(a_{iL} + b_{iL}w_i) - c_L(e_{iL}) + \beta \lambda_i e_i L \int \max \{ J_i(0, x), V_{iL}(w_i) \} dF(x) \]
\[ + \beta (1 - \lambda_i e_i L) V_{iL}(w_i) \]

In each state, the first order condition associated with the search efforts\(^4\) satisfies:

\[ c'_j(e_{ij}(\cdot)^*) = \beta \lambda_{ij} \int_{R_{ij}(\cdot)} (J_i(0, x) - V_{ij}(\cdot)) dF(x) \text{ for } j = N, P, L \]

(2)

with \(R_{ij}\) the reservation wage. As usual, the worker chooses the search efforts such that the marginal cost equals the marginal return. The optimal search strategy defines the reservation wage such that the value of employment at least equals the value of unemployment in state \(j\):

\[ J_i(0, R_{ij}(\cdot)) = V_{ij}(\cdot) \text{ for } j = N, P, L \]

Eventually, we need to define the value of a job. Our framework borrows from Burdett and Mortensen [1998] job search model and allows for job-to-job transitions, with a probability \(\lambda_{Ei}\), and job destruction, with a probability \(q_i\). To simplify the model and its estimation, both probabilities are exogenous. One of the special feature of our model, is that workers’s eligibility hinges on their employment spell duration. The value of a job with a wage \(w_i\) in an employment spell with an elapsed duration \(t_i\) reads:

\[ J_i(t_i, w_i) = u(w_i) + \beta \lambda_{Ei} \int_{w_i} (J_i(t + 1, x) - J_i(t + 1, w_i)) dF(x) + \beta q_i V_{iN}(t_i + 1, w_i) \]
\[ + \beta (1 - q_i - \lambda_{Ei} \bar{F}(w_i)) J_i(t_i + 1, w_i) \]

Notice that the model (and its estimation) would be much simpler if we assumed \(J_i(w_i) = w_i/(1 - \beta)\). However, this would be an important simplification, especially for workers with a high destruction rate (especially the unskilled workers).

3 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, these effects are not standard for two reasons. First, the effort devoted in the claim and the job search interact. A change which increases the incentives to claim for benefits can decrease the job search intensity. Second, as already noticed by Mortensen [1977], the eligibility depends on the employment duration. Even if a worker does not expect to be eligible, he is affected by the unemployment insurance. In the following, we investigate the link between job search and claiming strategies in the case an increase of the unemployment benefit

\(^4\)To simplify the presentation, we assume that the effort cost is high enough such that the sum of the probabilities is always lower than one. On the contrary, the simulations and estimation of the model account for this constraint. A continuous time framework with Poisson arrival rate would be a simpler way to encompass these competing events. However, we need to solve the model by iteration on the value functions and we thus need a discrete time framework.
ratio $b_P$, the effects of a rise of the insurance duration being similar. To simplify, we assume the cost functions to be quadratic: $c(.) = (1/2)c(.)^2$.

**The eligibility effect.** Consider an unemployed worker who thinks that he is not eligible ($P(t_i) = 0$) or who has exhausted his unemployment benefits (he is in state $L$). What is the effect of an increase in the unemployment benefit ratio $b_P$? Using the optimality conditions one gets:

$$\frac{\partial e_N(0, w_i)}{\partial b_P} > 0 \quad \text{and} \quad \frac{\partial R_{iN}(0, w_i)}{\partial b_P} < 0$$

$$\frac{\partial e_L(w_i)}{\partial b_P} > 0 \quad \text{and} \quad \frac{\partial R_{iL}(w_i)}{\partial b_P} < 0$$

Of course, there is no direct effect since the worker cannot receive any unemployment compensation during his current unemployment spell. However, the value of being employed increases since future unemployment spell are better insured. Hence the exit rate from unemployment increases.

**Opposite effects on the claiming and job search efforts.** What is the effect for workers who have just been laid off and for whom $P(t_i) > 0$? Remember that, in our model, the value of employment includes the probability to lose the job and to be unemployed. To put aside this mechanism, we temporary assume that the reemployment probability to be fired after is zero: $q_i = 0$. Using equation (2) and the value functions, one gets

$$\frac{\partial e^*_i}{\partial b_P} = -\beta \frac{\lambda_i F(R_{iN}^*) \partial V_i}{2 c_N}$$

$$\Rightarrow \frac{\partial e^*_i}{\partial b_P} = -\beta \lambda_i F(R_{iN}^*) \frac{\partial V_i}{2 c_N} \frac{c_N \partial \delta^*_i}{\partial b_P}$$

and, in the same way,

$$\frac{\partial \delta^*_i}{\partial b_P} = \beta P(t_i) \frac{\partial V_i}{\partial b_P} + 2 c_N e^*_i \frac{\partial e^*_i}{\partial b_P}$$

combining these two equations, one shows that

$$\frac{\partial e^*_i}{\partial b_P} > 0 \quad \text{and} \quad \frac{\partial e^*_i}{\partial b_P} < 0$$

Besides, it is easy to show that the rise of $b_P$ increases the reservation wage $R_{iN}$. Since the worker thinks that he will never lose his job again after reemployment, an increase in the reemployment rate does not affect the value of employment. However, it decreases the exit rate from unemployment by rising the value of unemployment. The worker postpones his job search to state $P$ and increases his claiming effort since the unemployment insurance is more profitable.

**The ambiguous effect of the unemployment insurance on the exit rate from unemployment.** What happens now when the worker takes into account the increase in the unemployment
value and the eligibility effect (the increase in the reemployment value)? The overall effect is then ambiguous. Especially, it depends on the worker’s expectations about his present eligibility status. A low probability to be eligible induces a low value of the current unemployment period and a small direct effect of a change in the unemployment insurance generosity. The consequences of such a change are mainly due to its effect of the value of reemployment since it decreases the cost of the future unemployment periods. The UI generosity can, in this case, increase the exit rate from unemployment. On the contrary, if the worker’s probability to be eligible is high, higher unemployment benefits or a longer unemployment compensation decrease the exit rate from unemployment in state \( N \) but increases the take-up.

**Implications for the empirical analysis.** From these simple examples, it becomes obvious that the take-up and the job search behavior both interact. In some case, the rise in the incentives to make a claim decreases the exit rate from unemployment because the worker postpones his job search. If we want to estimate the determinants of the take-up and evaluate the effects on welfare of changes in the UI design, this interaction must be taken into account. We also demonstrate that the imperfection of information on eligibility rules can be crucial. It affects dramatically the job search strategies. By estimating the model structurally, we consider these issues carefully.

### 4 Empirical Application and Estimation Method

Our structural model does not deliver analytical solution for the endogenous variables. We choose to estimate it using indirect inference (Gouriéroux, Monfort and Renault (1993)). We begin this section by presenting the data and the selected sample, then we discuss the estimation technics.

#### 4.1 The data

We estimate our model using data from the French Labor Force Survey (“Enquête Emploi”) between 2003 and March 2007\(^5\). This survey is a 18 months rotating panel of individual trajectories similar to the American CPS. People are interviewed every three months and report, on a monthly basis, labor market transitions which occurred during the previous months. The short interval between two interviews limits memory problems and provides a reliable calendar of activity. At each interview, the workers declare whether they have a job or not, their elapsed duration in the current state and their previous job duration. During the first interview, they also report their labor market status for each month of the previous year. We use these informations to rebuild the individual trajectories on the labor market. We can thus determine the eligibility status at the time of job loss and define the variable \( t \) on which the worker bases his eligibility expectations (the \( P(t) \) function). Moreover, when a worker is unemployed and receives unemployment benefits we know the date of entry in unemployment and of registration (even if it occurred before the first interview). We thus observe the (censored) take-up decision and the duration without and with compensation. When s/he is unemployed but non-recipients, s/he reports the reason why s/he does not receive benefits.\(^5\)

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\(^5\)Between January 2003 and March 2007 the design of the unemployment insurance system has been unchanged. Before and after, the entitlement rules were different. Our model is not designed to take such a change into account.
Finally, the survey includes information about current (past when unemployed) and reemployment wages.

We restrict the analysis to the spells for which the worker is aged under 50 at the time of entry into unemployment. Older workers have specific entitlement rights and their decision set is complex. Our data set does not provide sufficient information to determine the eligibility in this case. For workers under 50, the entitlement to unemployment benefits hinges on the number of days the worker were affiliated to the unemployment insurance whatever the number of hours. A worker who has worked more than six months during the last 22 months is eligible. Depending on their past employment duration, workers can be entitled to seven or twenty-three months of unemployment insurance (see Table 6 in Appendix).

For some individuals, the calendar of activity and the retrospective informations are not sufficient to determine their eligibility status. We discard these observations. However, if compare in term of gender, education and age (see Table 3) the entitled workers population and the population of workers with an uncertain status are very similar. The selection we impose on the data is thus probably limited. The final sample consists of 1970 unemployed workers entitled to the UI. We follow theses workers from their entry in state $N$ to the job transition if any, including transition in state $P$. Since workers are only followed during 18 months, we do not observe a sufficient amount of transitions to state $L$. We are thus not able to estimate the associated parameters. For that reason, we assume that this state is equivalent to state $N$ when the worker is not eligible ($V_N(0,w)$).

Table 4 describes the composition of the sample. 13% of the individuals are entitled to the first type of insurance and 58% to a longer insurance duration. For the remaining 29% we are uncertain about the duration they are entitled to.

Finally, we classify as recipient an individual who is entitled to the benefit and reports a date of registration at the national unemployment agency. The level of non take-up is in the range of the rates estimates for other countries using administrative data (Anderson and Meyer [1997], DWP [2008]).

Table 5 shows the characteristics of the recipients and non recipients entitled populations. Only 61% of the eligible workers receive unemployment benefits during their unemployment spell. The longer the compensation duration they are eligible for, the higher the take-up rate: 57% of the workers not entitled to the second type of insurance receive the benefits versus 67% of those who are observed as entitled to the longest benefit duration (the observed take-up rate is 56% for those who are uncertain about their entitlement to the second type of insurance). Men and young workers are more represented among the taker population. The past employment duration is on average longer for the individuals who are registered at the national agency.

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6 For those who do not have a sufficient number of days, an alternative rule counts the number of hours. Nevertheless, it is very unlikely that the worker satisfies this second criterion if he does not fulfill the first one.

7 Especially, notice that the unemployed only report the duration of their previous job and not the sum of all the employment periods last two years.

8 Administrative data give a similar repartition between the different types of insurance.
4.2 Indirect inference

Outline. Indirect inference is a generalization of the method of simulated moments. The underlying idea is to find the vector of the structural parameters, \( \hat{\theta} \), that minimizes the distance between a given set of moments of the real data, noted \( \beta_r \), and the model-predicted counterparts of these moments based on artificial data obtained by simulation of the structural model, \( \beta_s(\theta) \). Formally

\[
\hat{\theta} = \arg\min_{\theta} [\beta_r - \beta_s(\theta)]^T \Omega [\beta_r - \beta_s(\theta)]
\]

where \( \Omega \) is a symmetrical nonnegative matrix, for example the inverse of the variance-covariance matrix of moments of the real data or the identity matrix. Indirect inference only requires that the structural model can be simulated given a value of the parameter vector, \( \theta \). To that end, functional form assumptions about the utility function \( u(\cdot) \), the wage distribution \( F(w) \), the perceived probability to be eligible \( P(t) \) are needed.

It is worth noting that the way we generate simulated data must conform with the limitation of the real dataset. Hence, the population of workers must have the same distribution of observables characteristics (including past wages and past employment durations). During the estimation, each worker in the dataset has \( S \) simulated equivalents with the same characteristics. Notice that our panel is unbalanced. Because the workers are followed starting from their entry in state \( N \), some workers are potentially observed during a limited number of periods. Indirect inference offers a natural solution to that problem. For each worker, we impose the same number of potential observation periods as in the data.

Specification. 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. Then these values are needed to simulated individuals trajectories which are used to compute the moments. Since our structural model cannot be solved analytically in the general case we use value function iteration to solve it. To make the estimation tractable, we stratify our sample by education and consider two groups of workers: “high”-skilled (>undergraduate) and “low”-skilled (<undergraduate) workers (respectively 580 and 1149 observations). The model is estimated on each group separately. Next version of the paper should include more heterogeneity by allowing the parameters to be functions of workers’ observable characteristics.

The utility function reads \( u(x) = \log(x) \) and the discount rate \( \beta \) is set to .995. We discretize the wage support: we draw 300 wages in the observed wage distribution and use them as a wage grid. When a wage does not equal any point on the grid, we use spline interpolation to obtain the worker’s optimal efforts (see Adda and Cooper [2002] for an introduction to the interpolation methods in dynamic programming). Log-wage offers are assumed to be randomly drawn from a Weibull distribution truncated from below with cdf.
\[ F(w) = 1 - \exp \left( - \left( \frac{w - wp_3}{wp_1} \right)^{wp_2} \right) \]

with positive parameters \( wp_1 \) and \( wp_2 \). To reduce the number of parameters to estimate, we set the truncation point, \( wp_3 \), to the minimum wage observed in our sample. Within a strata, all workers face the same offer distribution. Nonetheless, notice that their reservation can be different. For workers without information about the wage in their previous job, \( w^p_i \), we use the value predicted by a linear wage equation estimated on the unemployed’s observed wages. In the same way, if the reemployment wage \( w^r_i \) is not observed, we use the prediction made using the observed reemployment wages.

Finally, we limit the possible values of \( t \) for which the intertemporal values in state \( N \) can be different. For the moment, \( t \in [0,18] \), which means that workers with more than 17 months of employment duration expect to be eligible with probability one. The perceived probability to be eligible, \( P(t) \), reads

\[ P(t) = p_1 \times \frac{t}{5} \quad \text{for } t \in [0,5] \]
\[ P(t) = p_2 + (1 - p_2) \times \frac{t - 6}{12} \quad \text{for } t \in [6,18] \]

with \( 0 \leq p_j \leq 1 \) the determinant of the slope of the function. This specification encompass the perfect information case, in which \( p_1 = 0 \) and \( p_2 = 1 \). Because of the existence of special case in the eligibility rules we can never be sure that a worker is not eligible. For that reason, our sample only consists of workers for whom \( t \geq 6 \). Hence \( p_1 \) cannot be identified. We fix it to 0 which means that an unemployed knows that he cannot be eligible with less than 6 months of employment. \( p_2 \) is the only parameter to be estimated. If it is estimated lower that 1, it would mean that the information about the rules isn’t perfect.

Recall that the job destruction rate is assumed to be exogenous and thus does not hinge on any other structural parameters. To reduce the parameters’ space, we choose to estimate it separately using a time-independent discrete duration model\(^{10}\).

### 4.3 Auxiliary models and identification

The choice of auxiliary models, i.e. the choice of which moments to match is a crucial step in the indirect inference approach. These moments are chosen to reflect the link between the structural parameters and the individual choices.

**A duration model.** The first set of moments is the estimates of a simple duration model in discrete time. There are three possible states: two unemployment states \( N \) and \( P \), and employment \( J \). We record transitions from unemployment to job (\( N \rightarrow J \) and \( P \rightarrow J \)) and between the two unemployment states (\( N \rightarrow P \)). The probabilities for a worker \( i \) to make a transition, at each period, read

\(^{10}\)We hope to estimate the full model but prefer at this stage to reduce the numerical complexity
\[
\begin{align*}
    \text{Prob}(N \rightarrow P|i) &= \frac{\exp(\alpha_{NP})}{1 + \exp(\alpha_{NP} + X'_i Z_{NP}) + \exp(\alpha_{NJ} + X'_i Z_{NJ})} \\
    \text{Prob}(N \rightarrow J|i) &= \frac{\exp(\alpha_{NJ} + X'_i Z_{NJ})}{1 + \exp(\alpha_{NP} + X'_i Z_{NP}) + \exp(\alpha_{NJ} + X'_i Z_{NJ})} \\
    \text{Prob}(P \rightarrow J|i) &= \frac{\exp(\alpha_{PJ} + X'_i Z_{PJ})}{1 + \exp(\alpha_{PJ} + X'_i Z_{PJ})}
\end{align*}
\]

\(X\) include worker’s past wage and employment duration. Workers are supposed to be followed until their transition in employment (if any) and we record duration in each states. The model is estimated by maximum likelihood.

This simple duration model helps to identify the transition parameters but is also designed to capture the \(P(t)\) parameters. Indeed, notice that the identification of these parameters is achieved through variation in the exit rate from state \(N\) to job with respect to \(t\). The idea is the following. In the case of perfect information about the eligibility rules, two workers with \(t = 6\) and \(t = 7\) and the same wage should have the same exit rate from unemployment. If it is not the case, it means that \(P(6) \neq P(7) \leq 1\). This auxiliary model is designed to capture this effect. Indeed, if workers’ information about the eligibility rules was perfect, the exit rate of workers with identical eligibility statuses should follow the same probability distribution.

We also include raw moments of the unemployment durations: the mean and standard deviation for the durations in states \(N\) and \(P\).

\textbf{Reemployment wage equations.} Reemployment wages depend on the reservation wages and thus on all structural parameters. For that reason, their variations convey useful informations. We include two reemployment wage equations estimated by OLS: one using wage observations for workers moving from \(N\) to \(J\) and another one for workers coming from insured unemployment. In both cases, we consider past wages as explanatory variable. For workers coming from \(N\) we also include past employment durations since, in our model, it affects reservation wage through \(P(t)\). Notice, that the parameters which link the instantaneous utility with the wage in the previous job are identified through variation in the transition rates AND reemployment wages with respect to past wages. Both the the unemployment durations and the reemployment wages distributions convey useful informations.

Finally, to pin down the job offers distribution’s parameters we include the mean, the standard deviation, the skewness and the kurtosis of the \(N\) and \(P\) reemployment wages.

\section{5 Results}

A former version of the paper provides results using MLE. We present these results in the appendix.

\section{6 Discussion}

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Appendix - An Estimation of the Model Using ML

A previous version of the model was estimated by maximum likelihood. We present the method and the preliminary results we obtained.

**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 duration $D_{ij}$ in months in each state. If the worker finds a job, we also observes his reemployment wage.

Consider a worker $i$. Assume that we can assess his eligibility with certainty. 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:

$$
\ell_i(D_{iN}, D_{iP}, D_{iL} = 0, w_i, w_i^p, t_i, X_{io}) = \gamma_i \delta_i^* \times (1 - \lambda_i \epsilon_i^* \tilde{F}(R_{iN}^*) - \gamma_i \delta_i^*)^{D_{iN} - 1} \\
\times (1 - \lambda_i \epsilon_i^* \tilde{F}(R_{iP}^*) - \mu_i)^{D_{iP} - 1} \times \lambda_i \epsilon_i^* \times f(w_i)
$$

This equation deserves some comments. First, the effective claiming success do not depend directly on $P(t_i)$ since this function only represents the expectation of the worker and not necessary the real eligibility. However, it affects the transition through its effect on the search and claiming effort $\epsilon_i^*$ and $\gamma_i$. Second, recall that the optimal values depend on the structural parameters and the worker’s characteristics. The other contributions are similar and easily derived from the model.

**MC experiment** To assess the ability of our estimation strategy to identify the structural parameters, we made a small Monte-Carlo experiment. We create by simulation of a dataset of 2000 workers. We fix the job-to-job transition and the job destruction rate and estimate using MLE. We do this 500 times. Table 1 present our results. All mean estimates match the true values. However, we see that on limited sample size the sd of $\alpha$ are large. For this reason, we drop this parameter in the following estimation.

**Results**

We present in Table 2 the estimated structural parameters obtained using the sample of the entitled population, i.e. of the individuals who are observed on employment during at least 6 months before their entry into unemployment. Remember that we use a simplified version of the model, without job-to-job transition and without $L$ state. Moreover, we reduce the set of parameters further by assuming that the workers know that their probability to be eligible is zero for employment durations lower than six months ($p_1=0$) and by putting the constant in the utility functions ($a$) to zero. Due to discontinuity in the log likelihood around the estimates, the s.d. cannot be obtained with the usual approximation of the variance-covariance matrix. This discontinuity comes from the fact that the contribution to the likelihood of an individual can tend to zero (and thus minus infinity in log) for values of the parameters close to the estimates. To compute the standard errors,
Table 1: Monte Carlo simulations

<table>
<thead>
<tr>
<th>True value</th>
<th>Mean est.</th>
<th>s.d.</th>
</tr>
</thead>
<tbody>
<tr>
<td>Transition parameters</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\lambda_N$</td>
<td>0.1</td>
<td>0.1158 (0.0109)</td>
</tr>
<tr>
<td>$\lambda_P$</td>
<td>0.2</td>
<td>0.1973 (0.0216)</td>
</tr>
<tr>
<td>$\lambda_L$</td>
<td>0.1</td>
<td>0.1027 (0.0171)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.3</td>
<td>0.3111 (0.0668)</td>
</tr>
<tr>
<td>$\mu$</td>
<td>0.1</td>
<td>0.0943 (0.0036)</td>
</tr>
<tr>
<td>Instantaneous utilities</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$a_N$</td>
<td>0.05</td>
<td>0.0593 (0.0390)</td>
</tr>
<tr>
<td>$b_N$</td>
<td>0.2</td>
<td>0.2087 (0.0387)</td>
</tr>
<tr>
<td>$a_P$</td>
<td>0.05</td>
<td>0.0486 (0.0261)</td>
</tr>
<tr>
<td>$b_P$</td>
<td>0.45</td>
<td>0.4323 (0.0533)</td>
</tr>
<tr>
<td>$a_L$</td>
<td>0.05</td>
<td>0.0468 (0.0147)</td>
</tr>
<tr>
<td>$b_L$</td>
<td>0.2</td>
<td>0.2049 (0.0475)</td>
</tr>
<tr>
<td>Job offer distribution</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\nu_1$</td>
<td>25</td>
<td>25.004 (0.0687)</td>
</tr>
<tr>
<td>$\nu_2$</td>
<td>10</td>
<td>9.994 (0.1832)</td>
</tr>
<tr>
<td>Eligibility prob. function</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>0.5</td>
<td>0.5015 (0.0542)</td>
</tr>
</tbody>
</table>

we need to approximate the hessian. This numerical approximation can be tricky in this case. One solution would be to bootstrap. This has not be done yet. The results are thus preliminary and are displayed for illustration purpose.

Table 2: Results

<table>
<thead>
<tr>
<th>Unskilled</th>
<th>Skilled</th>
</tr>
</thead>
<tbody>
<tr>
<td>Est.</td>
<td>s.d.</td>
</tr>
<tr>
<td>Replacement rates</td>
<td></td>
</tr>
<tr>
<td>$b_N$</td>
<td>0.118 (-)</td>
</tr>
<tr>
<td>$b_P$</td>
<td>0.793 (-)</td>
</tr>
<tr>
<td>Misperception</td>
<td></td>
</tr>
<tr>
<td>$p_2$</td>
<td>0.906 (-)</td>
</tr>
<tr>
<td>Claiming frictions</td>
<td></td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.137 (-)</td>
</tr>
<tr>
<td>Frictions</td>
<td></td>
</tr>
<tr>
<td>$\lambda_{0N}$</td>
<td>0.328 (-)</td>
</tr>
<tr>
<td>$\lambda_{0P}$</td>
<td>0.448 (-)</td>
</tr>
</tbody>
</table>

The parameters $b_N$ and $b_P$ capture the link between the previous wage and the instantaneous utility in state $N$ and $P$. For a given wage level, unskilled workers benefit from higher instantaneous utilities than the skilled ones. It is worth noting that these estimates seem reasonable when compared with the actual UI rules. Indeed, the replacement rates varies from 57% to 75%. The
rules are such that lower wages get a higher replacement rate. Moreover the wage used to determine the unemployment benefits is not necessary the exact previous wage since it excludes some form of compensation. The “real” replacement rate can thus be lower that the official replacement rate. Notice that the differences between the two groups reflect also that that unemployment may be experienced differently according to the individual characteristics. If stigmatization is higher for high skilled workers, they could suffer more from being unemployed. This would lower the subjective replacement rates we estimate.

The estimations confirm the theoretical hypothesis of a change in the job search technology between the unemployment states. The job search is indeed more effective when insured, for both skill levels. This might be due to the positive impact of counseling and job search assistance provided by caseworkers.

The misperception of the eligibility rules appears rather limited, as the estimated parameter $p_2$ of the probability function is close to 1, case where there is no imperfect information. The skilled workers seem more subject to misperception than the unskilled. However, without standard errors, we don’t know if this difference is significant. While the imperfection of information about the rules is limited, the frictions in the claiming process are important and similar for both groups. The job search and the claiming frictions are represented in the same way in the model. The index of claiming frictions is three time lower which mean the claiming frictions are at least as important as the job search frictions. For a similar efforts and costs devoting in both activities, the monthly probability to find a job is three times higher than the probability to end in insured unemployment.

These early results indicate a limited misperception of the eligibility rules, but a real complexity in the claiming process. The UI take-up could then be increased by simplifying the claiming process.
References


Hernanz V., Malherbet F. and Pellizari M. [2004], “Take-up of Welfare Benefits in OCDE Countries: A Review of the Evidence”, OCDE.


### Table 3: Sample Selection

<table>
<thead>
<tr>
<th></th>
<th>Entitled population (entitled for sure)</th>
<th>Rest of the data set (uncertain status)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>1970</td>
<td>1242</td>
</tr>
<tr>
<td>% of the sample</td>
<td>61.6</td>
<td>38.7</td>
</tr>
<tr>
<td>% Female</td>
<td>47.0</td>
<td>50.6</td>
</tr>
<tr>
<td>% Unskilled</td>
<td>66.14</td>
<td>65.5</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% 16-30</td>
<td>44.7</td>
<td>44.8</td>
</tr>
<tr>
<td>% 30-40</td>
<td>32.3</td>
<td>31.2</td>
</tr>
<tr>
<td>% 40-50</td>
<td>23.0</td>
<td>24.0</td>
</tr>
</tbody>
</table>

### Table 4: Characteristics of the sample by entitlement status

<table>
<thead>
<tr>
<th>Entitled population</th>
<th>All the eligibles</th>
<th>Type-1 uncertain type (1 or 2)</th>
<th>Type-2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>1970</td>
<td>254</td>
<td>578</td>
</tr>
<tr>
<td>% of the sample</td>
<td>100</td>
<td>13</td>
<td>29</td>
</tr>
<tr>
<td>% Female</td>
<td>47</td>
<td>52</td>
<td>45</td>
</tr>
<tr>
<td>% Unskilled</td>
<td>66</td>
<td>66</td>
<td>66</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>% 16-30</td>
<td>45</td>
<td>52</td>
<td>51</td>
</tr>
<tr>
<td>% 30-40</td>
<td>32</td>
<td>26</td>
<td>30</td>
</tr>
<tr>
<td>% 40-50</td>
<td>23</td>
<td>22</td>
<td>19</td>
</tr>
<tr>
<td>Mean past empl. duration</td>
<td>19</td>
<td>8</td>
<td>10</td>
</tr>
<tr>
<td>Duration in state N</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>3.1</td>
<td>2.7</td>
<td>4.1</td>
</tr>
<tr>
<td>standard error</td>
<td>4.2</td>
<td>3.6</td>
<td>5.3</td>
</tr>
<tr>
<td>Q1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>median</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>Q3</td>
<td>3</td>
<td>3</td>
<td>5</td>
</tr>
</tbody>
</table>
Table 5: **Composition of the sample by take-up status**

<table>
<thead>
<tr>
<th></th>
<th>Non Takers</th>
<th>Takers</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of observations</td>
<td>764</td>
<td>1206</td>
</tr>
<tr>
<td>% of the sample</td>
<td>38.8</td>
<td>61.2</td>
</tr>
<tr>
<td>% Female</td>
<td>49</td>
<td>46</td>
</tr>
<tr>
<td>% Unskilled</td>
<td>66</td>
<td>66</td>
</tr>
<tr>
<td>Age</td>
<td></td>
<td></td>
</tr>
<tr>
<td>% 16-30</td>
<td>42</td>
<td>47</td>
</tr>
<tr>
<td>% 30-40</td>
<td>34</td>
<td>31</td>
</tr>
<tr>
<td>% 40-50</td>
<td>24</td>
<td>22</td>
</tr>
<tr>
<td>Past empl. duration</td>
<td></td>
<td></td>
</tr>
<tr>
<td>mean</td>
<td>17</td>
<td>21</td>
</tr>
<tr>
<td>standard error</td>
<td>12.1</td>
<td>14.7</td>
</tr>
<tr>
<td>Q1</td>
<td>10</td>
<td>11</td>
</tr>
<tr>
<td>Q2</td>
<td>13</td>
<td>16</td>
</tr>
<tr>
<td>Q3</td>
<td>20</td>
<td>24</td>
</tr>
</tbody>
</table>

Table 6: **Entitlement for unemployment benefits (January 2003 - January 2006)**

<table>
<thead>
<tr>
<th>Age and work activity</th>
<th>Maximal length of compensation</th>
</tr>
</thead>
<tbody>
<tr>
<td>6 months of work during the past 22 months</td>
<td>7 months</td>
</tr>
<tr>
<td>14 months of work during the past 24 months</td>
<td>23 months</td>
</tr>
<tr>
<td>over 50 year-old</td>
<td></td>
</tr>
<tr>
<td>27 months of work during the past 36 months</td>
<td>36 months</td>
</tr>
<tr>
<td>over 57 year-old</td>
<td></td>
</tr>
<tr>
<td>27 months of work during the past 36 months</td>
<td>42 months</td>
</tr>
<tr>
<td>100 trimesters of old age pension</td>
<td></td>
</tr>
</tbody>
</table>