Counseling the unemployed: does it lower unemployment duration and recurrence?*

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Abstract

In July 2001, the French unemployment policies experienced an important reform. As a major input of this reform, the public unemployment agency (ANPE) revised its support policy to unemployed persons within the Programme d'Action Personnalisée (PAP). Individual follow-up became systematic and more frequent overall, and significantly larger amounts of job-search assistance services were provided. This reform departs from most foreign policies in that very intensive schemes are attributed to a rather modest share of the unemployed, whereas limited actual monitoring seems to have been taking place. In this study, we evaluate the effectiveness of the PAP services in raising the transition rate from unemployment to work and lowering recurrence into unemployment. We exploit an administrative database collected by the French unemployment agency that contains data on more than 500,000 individual unemployment spells and very detailed information on services that individuals actually received. The available timing of events allows identificatio of the causal effects of the schemes in the presence of selectivity on unobservables. We find that three out of the four main schemes evaluated are efficient in lowering both unemployment duration and recurrence, with a lock-in effect for some of them. However, the rather limited number of beneficiaries affects the aggregate impact of the program.

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1 Introduction

Among active labor market policies that are believed to have some impact on labor market transitions, increasing attention has been devoted to job-search assistance combined with monitoring of the unemployed. Several schemes have been implemented in OECD countries during the 1990's, sometimes in conjunction with generous benefit systems, as in Denmark, or with sharper sanctions, as in the Netherlands or U.K. Evaluation of this class of policies has led to mixed conclusions, implying that efficiency is subject to actual implementation and may be sensitive to macroeconomic conditions (Martin and Grubb, 2001, van den Berg and van der Klaauw, 2003). Also, effects are potentially heterogenous with respect to sub-populations, implying that efficient targeting may have some impact on overall performances.

In July 2001, the French unemployment insurance system followed that line of action: a major reform, the Plan d'Aide au Retour à l'Emploi (PARE), introduced two main changes. On the one hand, the degressivity of unemployment benefits was suppressed. On the other hand, the public unemployment agency ("Agence nationale pour l'emploi", ANPE) revised its support policy towards unemployed person within the Plan d'Accompagnement Personnalisé (PAP). Although some individual assistance was present before that date, mostly in favour of the long-term unemployed, individual follow-up became general and more frequent overall, and significantly larger amounts of job-search assistance services were provided. This reform departs from most foreign policies in that very intensive schemes are attributed to a rather modest share of the unemployed (less than 20%), whereas limited actual monitoring seems to have been taking place.

In a previous work, we have evaluated the effect of the PARE on the aggregate exit rate out of unemployment controlling for business cycle changes (see Crépon *et al.*, 2002). Our estimates do not show any clear pattern. This finding can be driven by the two potentially conflicting components of the PARE reform: the suppression of degressivity may delay the transitions to employment, while the individual follow-up in the PAP scheme should stimulate the job finding rate. The incentive effect of degressivity in the French system has been well documented by Dormont *et al.* (2001). In contrast, the effect of job-search assistance has not been evaluated in its recent form. In this study, we concentrate on this second effect and evaluate the effectiveness of the PAP *services* in raising the transition rate from unemployment to work in France and lowering recurrence into unemployment. In the present setup, this can be evaluated independently from the own effect of monitoring and sanctions.

In some countries, controlled experiments are available (see van den Berg and van der Klaauw, 2003, for the Netherlands, Dolton and O'Neill, 1996, 2002, for U.K., Meyer, 1995, for a review of U.S. experiments). In the present context, neither such an experiment nor a quasi-experimental design is available, because the reform applies uniformly to all unemployed. Still, semi-parametric identification of causal parameters in the presence of selectivity on unobservables it possible relying solely on the timing of events (Abbring and van den Berg, 2003). This strategy has been successfully implemented in a set of recent papers (Abbring *et al.*, 2000, Lalive *et al.*, 2002, van den Berg *et al.*, 1999, van den Berg *et al.*, 2004 - see also Bonnal *et al.*, 1997, for an early model in that vein). In this paper, we exploit an exceptional administrative database collected by the French unemployment agency that contains data on more than 500,000 individual unemployment spells and very detailed information on services that individuals actually received, since implementation of the PARE until June 2003. These programs can last from 20 hours to 3 months and can either provide assessment of skills or assistance in job-search activities. The size of the data allows flexible estimation of the effects of four sets of schemes, including time dependance of the effects and heterogenous effects.

The plan of the paper is as follows. The next section details the 2001 reform of the French unemployment insurance and monitoring system. Section 3 presents a theoretical analysis of counseling. Section 4 describes the data. Section 5 presents the estimation method and estimation results are discussed in Section 6 and Section 7. The concluding part summarises our findings.

2 The unemployment policy reform in France in 2001

The reform introduced in France in July 2001 is influenced by foreign experiences (Freyssinet, 2002) but it has a strong specificity. The original project was to introduce a contractual relationship whereby the degressivity of the unemployment benefit was suppressed in exchange for stronger monitoring based on frequent interviews, along with extended provision of job-search assistance schemes. In practice, however, the contractual and monitoring side is limited. For one thing, the contractual relationship, although emphazised and formalized, is based on already existing legal requirements. For another, monitoring is delegated to the public unemployment agency (ANPE) that is distinct from the institution that manages unemployment benefits (UNEDIC): as a result, it is unclear that sanctions are more severely implemented.

The reform thus consists mainly of two elements: a more generous benefit system (for entitled unemployed) and significantly stronger counseling of the unemployed (whether insured or not), labelled the "PAP" program ("Programme d'action personnalisée"). Regarding search assistance, there are two main changes. First, it was not unusual that an unemployed person would never meet the public unemployment agency caseworkers. A meeting (typically 30 minutes long) is now compulsory for all newly registered unemployed and recurs at least every 6 months. This is a low frequency, but still in line with international averages (Martin and Grubb, 2001). It can come more often, however, depending on the person's profile and the 6 months timing is not strictly followed, in particular for the unemployed who belonged in the stock as of July 2001.

The second change lies in the significant extension of services that existed before the reform, at the cost of increased budget. Some are provided directly by ANPE, others are sub-contracted. Before the reform, these measures were open only to the long-term unemployed (more than a year). Training and employment subsidies are also in the range of measures proposed to the individuals but they are not considered in this paper.

During the first compulsory meeting, the unemployed person and the caseworker come together to an agreement about the degree of assistance that the person should receive. This agreement is based on the person's evaluation of his/her degree of autonomy in job search, the caseworker's evaluation of his/her capabilities of finding rapidly a job and the availability of slots in particular schemes. The interview ends with the signing of the PAP contract which determines the degree of assistance and the types of services the person will receive. The PAP contract also specifies the types of jobs corresponding to the skills of the individual in the occupation and region where he is searching for jobs as well as the types of jobs on which he is ready to reorientate his search. In the first interview, most of the unemployed workers are regarded as self-sufficient in their job search. The individuals who are considered not to have the skills to find work without assistance can follow, as soon as the first meeting, more intense job search assistance schemes. People are thus assigned an administrative category that determines the degree of monitoring and services he/she should receive. However, there is substantial variation in the treatments actually received within categories, so that proper evaluation of this policy should be based on observed services rather than theoretical categories. One important aspect is that the data on these treatments are systematically collected since the reform. We are interested in 4 types of schemes that group a larger number of services[1]: two are skill assessments and two are search assistance. The basic "Skill assessment" ("Evaluation") lasts up to 80 hours and can take place in the workplace. The provider helps the individual assess his professional skills for a precise job. Another skill assessment ("Bilan de compétence approfondi"), that we label "Project assessment", is aimed at individuals who experience difficulties to find a job corresponding to their skills. A personal adviser helps the individual to identify his skills and match them with a new employment project compatible with the state of the labor market. It lasts up to 20 hours during maximum 42 days. "Job-search support" ("Objectif emploi") is aimed at individuals having a well-defined employment project and lasts 3 months with the aim of finding rapidly a new job. Each individual is assigned a personal advisor who helps him define the course of action, teaches on job-search methods, provides logistic support, proposes job offers or interviews, contacts directly employers and so on. The bulk of the effort from ANPE is on this scheme. Finally, "Project support" ("Objectif projet") is aimed to individuals who wish or have to change profession, but need help to define a new employment project. The objective of this scheme is similar to "Project assessment" but it lasts 3 months and is more long-term oriented.

As can be seen from Table 1, only 17% of the unemployment spells in our data are associated with participation to at least one of these four programs over the whole period 2001-2004. A large majority of spells (80%) receive only one treatment. Among this group, Job-search support is by far the most frequent measure (44%). Figure 1 describes the empirical hazards into the schemes: peaks are related to compulsory interviews at 0, 6 and 12 months, but the entry rate remains positive at all dates and does not decline strongly in the long-run. The importance of Job-search support relative to other schemes is also visible in this figure.

INSERT FIGURE 1 APPROXIMATELY HERE

[1]These groups have been defined with the help of the ANPE statistics and research Department.

Although it benefits a limited number of persons, the cost of this programs is significant because of high unit costs. The unit cost of Job-search support and Project support is between 300 and 700 euros. In 2003, ANPE has spent about 440 million euros on these schemes. The unit cost of Project assessment is about 900 euros and that of Skill assessment is about 200 euros. The total cost of those assessment schemes was 180 millions euros in 2003. The schemes that are evaluated in this paper thus amount to approximately 0.04% of GDP which is about 20% of the total cost of public employment services. It can also be compared to the cost of the whole active labor market policy which is 1.25% of GDP (OECD, 2004).

INSERT TABLE 1 APPROXIMATELY HERE

3 Theoretical analysis of counseling

The theoretical effect of counseling (or other active labour market program such as training) has often been analysed within a job search model (see, e.g., van den Berg and van der Klaauw, 2003). This type of model is useful to investigate the effect of counseling on the exit rate from unemployment to employment. However, it fails to incorporate the effect of counseling on the characteristics of the job found after exit from unemployment. This question is important since our data allows us to measure the effect of the various PAP programs on the employment duration. This is the reason why we use a stochastic job matching model with endogenous job destruction à la Mortensen and Pissarides (1994) and Pissarides (2000). In such a model, the productivity of the job is made of two random component: a fixed component which is drawn after the match between the worker and the employer, and a varying component whose value changes with some probability. The central hypothesis of the model is that counseling increases the arrival rate of job offers. This assumption is quite standard (see, e.g., van den Berg and van der Klaauw 2003[2]) and seems appropriate for the analysis of counseling measures offered in the PAP scheme. Even if the intensity of search support depends on the type of program, the caseworker who is in charge of the program teaches on job search methods, proposes job offers or interviews with employers, contacts directly employers and proposes the application of the individual, etc. The theoretical development proceeds in two steps. In the first step, we assume exogeneous job destruction and we show that the effect of counseling on the exit rate from unemployment to employment. In a second step, we allow for endogenous job destruction and investigate whether participation to a counseling program contributes to a greater job stability. In both settings, we do not close the model and we leave the arrival rate of job offers exogeneous.

[2] Van den Berg and van der Klaauw (2003) make a distinction between job offers arriving through the formal channel (advertisements and public employment office) and the informal channel (employed worker, friend, relatives). They assume that counselling increases the arrival rate of job offers through the formal channel only.

3.1 Exogeneous job destruction

The essential hypothesis of the model is that counseling increases the arrival rate of job offers. Let us also assume, for simplicity, that the effect of counseling on the arrival rate is constant during the spell of unemployment (lasting beyond the participation period). Let $\lambda_{0,e}$ and $\lambda_{1,e}$ be the exogeneous arrival rates of job offers for the *non*-participants and participants to a counseling program with $\lambda_{1,e} > \lambda_{0,e}$. The unemployed worker enters into the participation state at the Poisson rate $\lambda_{0,1}$. We assume, again for simplicity, that the unemployment benefits b are state-independent.

The productivity of each job, denoted by y, is a random variable, drawn after the match between the unemployed worker and the employer in a cumulative distribution function (c.d.f.) $F_y(y)$ common to all jobs. As usual we introduce the function $Q_y(y) = \int_y^\infty (v - y)\, dF_y(v)$. All matches in which productivity y is below some reservation threshold, an endogenous variable y_{ci} which depends on the origin state $i = 0, 1$ of the worker (unemployment with participation or non-participation), do not result in the creation of a job. If the productivity y exceeds the reservation threshold, worker and employer then negotiate a wage $w_i(y)$ which also depends on the treatment status of the worker. Jobs are destroyed at the constant exogeneous rate q. If Π_v denotes the value of a vacant job, the expected profit from a filled job with productivity y, denoted by $\Pi_i(y)$, depends on the origin state of the worker and satisfies:

$$r\Pi_i(y) = y - w_i(y) + q(\Pi_v - \Pi_i(y)), \quad i = 0, 1 \tag{1}$$

The expected utility of an employee, denoted by $V_i(y)$, depends also on his state of origin and satisfies:

$$rV_i(y) = w_i(y) + q(V_{u0} - V_i(y)), \quad i = 0, 1 \tag{2}$$

where V_{u0} is the value of an unemployed person not participating to counseling. So we assume that the worker cannot directly enter a counseling scheme when he is fired.

The expected utilities of a unemployed worker not participating to a counseling scheme and a participant then satisfy:

$$rV_{u0} = b + \lambda_{0,1}(V_{u1} - V_{u0}) + \lambda_{0,e} \int_{-\infty}^{\infty} Max\,[V_0(y) - V_{u0}, 0]\, dF_y(y) \tag{3}$$

$$rV_{u1} = b + \lambda_{1,e} \int_{-\infty}^{\infty} Max\,[V_1(y) - V_{u1}, 0]\, dF_y(y) \tag{4}$$

The match surplus depends on the origin state of the worker and satisfies:

$$S_i(y) = V_i(y) - V_{ui} + \Pi_i(y) - \Pi_v, \quad i = 0, 1 \tag{5}$$

Proposition 1 : A job offer is accepted by previously treated (resp. not previously treated) workers if its productivity exceeds a threshold value y_{c1} (resp. y_{c0}). The reservation productivities satisfy:

$$y_{c1} > y_{c0} \text{ and } w\left(y_{c1}\right) > w\left(y_{c0}\right)$$

According to Proposition 1, participating to a counseling scheme induces workers to be more selective concerning productivity and wage of the job. Moreover if $\lambda_{0,1}$ and $\lambda_{1,e}/\lambda_{0,e}-1$ are small and of same order, the difference $y_{c1}-y_{c0}$ only depend on $\lambda_{1,e}/\lambda_{0,e}-1$.

Proof : see appendix 2

Proposition 2 : The untreated unemployed workers have a lower exit rate from unemployment to employment in an environment with counseling than in an environment without counseling:

$$\lambda_{0,e}\overline{F}_y\left(y^*\right) > \lambda_{0,e}\overline{F}_y\left(y_{c0}\right) \tag{6}$$

where y^* is the reservation productivity in an environment without counseling, Moreover if $\lambda_{0,1}$ and $\lambda_{1,e}/\lambda_{0,e}-1$ are small and of same order, the difference y^*-y_{c0} is of second order.

Proof : see appendix 1

Proposition 3 : If the distribution of productivity satisfies $\overline{F}_y^2\left(y\right)-Q_y\left(y\right)f_y\left(y\right) > 0$, then the treated unemployed workers have a higher exit rate from unemployment to employment than the untreated unemployed workers:

$$\lambda_{1,e}\overline{F}_y\left(y_{c1}\right) > \lambda_{0,e}\overline{F}_y\left(y_{c0}\right) \tag{7}$$

So, even if counseling makes workers more selective in their choice of jobs, this negative effect is not sufficient to reverse the positive effect of a higher arrival rate of job offers.

Proof : see appendix 3

Counseling leads to more productive and higher paid jobs. In spite of a higher selectivity in jobs (i.e. higher reservation wage), counseling also increases the exit rate from unemployment to employment of participants as compared to non-participants. Since it also induces non-participants to be more selective in their choice of jobs, the existence of counseling decreases the exit rate of non-participant as compared to an environment without counseling (provided that the transition rate to counseling programs, $\lambda_{0,1}$, is high enough and provided that counseling programs raise sufficiently the arrival rate of job offers). Counseling therefore contributes to increase the average productivity of jobs. To see whether counseling contributes to a greater job stability, we need to introduce endogeneous job destruction.

3.2 Endogeneous job destruction

Data on wages would be helpful to assess wether empirically there is an increase in the reservation productivity and wages. Another way to examine whether there is an increase in the reservation productivity is to examine whether jobs last longer. This is a natural idea that a more productive job will last longer. However in the context of the previous model job destructions are exogenous. We generalize the model to account for endogeneous job destruction and examine if the previous results generalize. The productivity of each job, denoted by $y+\varepsilon$, is now made of two random components. The random variable y is a constant characteristics of the job with the same property than above. The random variable ε is a varying characteristics of the job. It takes values in the support $]-\infty, \varepsilon_u]$, is distributed according to the c.d.f. $F_\varepsilon(\varepsilon)$ and takes a new value at the Poisson rate λ. We assume that all new matches start with $\varepsilon = \varepsilon_u$ but is eventually destroyed when a new value of ε arrives below some reservation threshold, an endogeneous variable $\varepsilon_d(y)$ which depends on the fixed productivity of the job. The destruction rate of a job y is therefore given by the rate $q(y)$ defined as:

$$q(y) = \lambda P(\varepsilon < \varepsilon_d(y)) = \lambda F_\varepsilon(\varepsilon_d(y)) \tag{8}$$

After worker and employer match, they discover the productivity y of the job and then negotiate a wage which is renegotiated when a new value of ε arrives. The negotiated wage $w(y+\varepsilon)$ depends on the total productivity of the job.

The value of a continuing job with productivity $y+\varepsilon$ for the firm is denoted by $\Pi(y+\varepsilon)$ and $V(y+\varepsilon)$ for the worker. Since y is fixed and workers have the same fallback position whatever their types, the values of a continuing job do no more depend on the origin state of the worker. They satisfy:

$$r\Pi(y+\varepsilon) = y+\varepsilon - w(y+\varepsilon) + \lambda(\Pi_\lambda(y) - \Pi(y+\varepsilon)) \tag{9}$$

where $\Pi_\lambda(y) = \int Max(\Pi(y+\varepsilon), 0) dG_\varepsilon(\varepsilon)$ is the expected value of the job for the firm with respect to the distribution of productivity shocks, and

$$rV(y+\varepsilon) = w(y+\varepsilon) + \lambda(V_\lambda(y) - V(y+\varepsilon)) \tag{10}$$

where $V_\lambda(y) = \int Max(V(y+\varepsilon), 0) dG_\varepsilon(\varepsilon)$ is the expected value of the job for the worker with respect to the distribution of productivity shocks

For a newly created job, the expected profit from the job depends on the origin state of the worker, as does the expected utility for the worker. The value of a newly created job with productivity $y(+\varepsilon_u)$ for a worker of type i is denoted by $V_i(y)$, the corresponding value for the firm is denoted by $\Pi_i(y)$. They satisfy:

$$r\Pi_i(y) = y + \varepsilon_u - w_i(y+\varepsilon_u) + \lambda(\Pi_\lambda(y) - \Pi_i(y)), \quad i = 0, 1 \tag{11}$$

$$rV_i(y) = w_i(y+\varepsilon_u) + \lambda(V_\lambda(y) - V_i(y)), \quad i = 0, 1 \tag{12}$$

The expected utilities of an unemployed worker not participating to a counseling scheme and a participant are the same than in the previous setting, equation (3) for V_{u0} and equation (4) for V_{u1}.

The match surplus of a newly created job depends on the origin state of the worker and satisfies:

$$S_i(y) = (V_i(y) - V_{ui}) + \Pi_i(y) - \Pi_v, \quad i = 0, 1 \tag{13}$$

The match surplus of a continuing job satisfies:

$$S(y+\varepsilon) = (V(y+\varepsilon) - V_{u0}) + \Pi(y+\varepsilon) - \Pi_v \tag{14}$$

Proposition 4: Results of proposition 1 and 2 carries over in the setting of endogenous job destruction.

Proof : see appendix 4

Proposition 5: The distribution of job destruction rates q of treated unemployed workers with c.d.f $G_1(q)$ dominates the distribution for non treated workers with c.d.f $G_0(q)$. duration of the first job after exit from unemployment is higher for treated unemployed workers than for untreated unemployed workers:

$$G_1(q) > G_0(q)$$

$$q(y_{c1}) = \lambda P(\varepsilon < \varepsilon_d(y_{c1})) < q(y_{c0}) = \lambda P(\varepsilon < \varepsilon_d(y_{c0})) \tag{15}$$

Proof: the proof consists in showing that $\varepsilon_d(y)$ is a decreasing function of y which is shown in appendix 4. Consider $y(q)$, the productivity level for which the destruction rate is q. $y(q)$ is defined by $q = \lambda F_\varepsilon(\varepsilon_d(y(q)))$. As long as $\varepsilon_d(y)$ is a decreasing function $q(y)$ will also be a decreasing function. Thus $G_1(q) = P_y(y > y(q)|treated) = \overline{F}_y(y)/\overline{F}_y(y_{c1})$ and $G_0(q) = P_y(y > y(q)|non\ treated) = \overline{F}_y(y)/\overline{F}_y(y_{c0})$. Therefore $G_1(q) > G_0(q)$ result from $\overline{F}_y(y_{c0}) > \overline{F}_y(y_{c1})$, that is $y_{c0} < y_{c1}$

Proposition 6: Results of proposition 3 carries over in the setting of endogenous job destruction under the condition that $\Phi^2 > \phi H$, where Φ is the cdf of $\varepsilon_d(y)$, ϕ its density and $H(\varepsilon) = \int\limits_{v<\varepsilon} (\varepsilon - v)\, d\Phi(v)$.

Proof : see appendix 5

4 Data and descriptive analysis

The empirical analysis is based on longitudinal data extracted from ANPE records. We use a 1/12 nationally representative sample of all unemployed persons[3] and we sample all inflow spells between July 2001 and September 2003. Data ends in June 2004 and unemployment spells are arbitrarily truncated at 900 days because information becomes very poor after that duration. The data contain a large number of individual characteristics and unemployment history can be traced because individual data is available

[3]The sample consists of all individuals born on March of an even year or October of an odd year. This sample, named "Fichier historique statistique" is updated routinely by ANPE.

back to 1993. Entry into and exit from unemployment are recorded on a daily basis, so that we model duration in continuous time. In this data, unemployment differs from the ILO notion in the sense that people are recorded as job seekers as long as they report so to ANPE on a monthly filled form, even if they have held occasional or short term jobs, which they have to declare. Some unemployed are classified as "not immediately available" because they suffer from health problems or cannot immediately drop their current occupation to take a job: the corresponding spells are not kept in the sample as well as that of the handicapped. We also truncate spells when the unemployed reaches 55.

Transitions may occur towards other destinations than employment but they will be treated as censoring, which implies that other destinations depend upon a disjoint subset of parameters. Although undesirable in some instances, this hypothesis maintains a tractable number of parameters to be estimated. In addition, some unemployed do not send their monthly form at some point so that they are known to exit but the destination is unobserved. As it would be incorrect to treat them as censored, we have dropped these observations: overall we are left with two third of the initial spells. As reported in Table 1, the whole sample (that is not entirely used in estimation) contains $516,821$ spells. The large amount of censoring (63%) is mainly due to the fact that exits to other destinations than employment (inactivity, training) are treated as censored.

The ANPE also provided data on the various schemes that the unemployed workers benefitted. They have been matched with the data on unemployment spells. Table 2 indicates that the assignment to the various measures is certainly not random. Column 1 gives some statistics on the characteristics of individuals who receive no treatment while columns 2 to 5 contain the same information for individuals who have participated to a given policy. Female, married with children and older individuals more often receive a treatment. This also holds for the beneficiaries of unemployment insurance. For beneficiaries of the minimum income (RMI), the effect is mixed.

When a transition from unemployment to employment takes place, we define an "employment duration" that is the time until the individual is back to reported unemployment. Because sampling is based on individuals and not spells, we are certain to observe the individual again in that case. Strictly speaking, the person may not have been in employment all the time, so that it is proper to consider that we measure more exactly recurrence. With respect to the objectives of ANPE, this is an important dimension.

INSERT FIGURE 2 APPROXIMATELY HERE

Figure 2 displays the empirical hazard rates of the exits to employment and unemployment. As usual, the unemployment-employment (U-E) transition exhibits a deceasing pattern with a small increase at one year that may be due to specific employment policies, including the ones considered here. The same pattern is found for the employment-unemployment (E-U) transition, with peaks at 6 and 12 months that may be related to standard contract durations.

5 Measuring the effect of counseling in a duration model framework

The causality analysis developed by Abbring and van den Berg (2002, 2003) is suitable for the estimation of a causal effect of the different programs offered in the PAP scheme. The methodology consists in modelling jointly the assignment process to programs and the exit to work. These processes are assumed to be correlated through a factor of unobserved heterogeneity and a direct effect of the programs on the exit rates to employment. Abbring and van den Berg show that the elapsed duration before treatment contains useful information to disentangle the causal effect of treatment from the effect induced by selection on unobservables. The intuition is that the competing hazard model until entry in a treatment or exit to employment - whichever occurs first - identifies the joint distribution of the unobservables. The remaining duration identifies the causal effect of the treatment. The exact timing of events is important because the causal effect is revealed by the change in the unemployment hazard rate that may occur once treatment is received.

Identification requires that the durations before treatment be well measured and vary sufficiently. It implies that we should observe individuals at different dates of entry into treatment. As shown in Figure 1, this condition is fulfilled in our data. Furthermore, for a causal effect to be identified from the data, unemployed individuals must not anticipate the date at which they will enter into a particular program. Otherwise, the program would have some effect before actual participation. However, such anticipation seem unlikely within the PAP scheme. The prescription of programs is made during the regular meetings at ANPE. The decision to send an unemployed worker to a program depends greatly on the agent in charge of the case and on the number of slots available, so that the individual never knows with certainty before the meeting if he will be offered to participate in a program. Besides, the time between the prescription of a program and its effective start is very short, preventing anticipation behaviour. Variability in the dates of entry into treatment and the absence of anticipation effect are sufficient to identify the causal effect of treatment when individuals experience multiple spells. In the absence of multiple spells, an additional identification condition is needed: observed and unobserved individual characteristics must affect proportionally the exit rate from unemployment to work. As shown in Table 1, we observe multiple spells for some individuals. However, this feature of the data is not exploited at this stage of the research. We assume a multivariate mixed proportional hazard model in which unemployment spells are independent for the same individual.

5.1 Benchmark model

The empirical model distinguishes the four types of treatment presented above. We index them with $P \in \{0, 1, 2, 3, 4\}$, where 0 stands for no treatment. There are thus six possible states: unemployment before any treatment, employment, which is an absorbing state for the moment, and unemployment with any of the four possible treatments being or having been undertaken. Individuals enter unemployment (U) and exit to one of the other states (unless their spell is censored). Because (in this version of the paper) we restrict the sample to spells with at most one treatment, people in one of the treatment states may then only exit to E (before censoring). We model the set of durations following recent papers by Abbring and van den Berg (2002, 2003) and Lalive, van Ours and Zweimüller (2000). We model the assignment to treatment as a competing risk model. The effect of treatment is defined as a change in the exit rate from unemployment to employment. This effect may depend on the characteristics of individuals and may vary with the elapsed duration since entry into treatment.

We consider three durations: t_U, the total duration unemployed, t_P the duration until treatment, t_R the residual duration since entry into treatment. These durations are linked through the following relationship: $t_U = t_P + t_R$. For individuals without treatment, $t_R = 0$, so $t_U = t_P$.

We model the hazard rate from unemployment to employment, conditional on the set of observable characteristics x, the duration t_P until treatment, the received treatment P, and a set of unobservable characteristics $v = (v_U, v_1, v_2, v_3, v_4)$ that affect the duration in employment and the assignment to treatment, as:

$$h_U(t|t_P, P, x, v_U) = \theta_U(t)\psi_U(x)v_U \prod_{k=1}^{4} \left[\delta_k(t - t_P)\varphi_k(x)\right]^{1(P=k)} \tag{16}$$

The functions $\theta_U(.)$ and $\psi_U(.)$ represent respectively the baseline hazard and the effect of observable characteristics on the conditional hazard. The term within square brackets captures the treatment effect which may shift the hazard rate differently according to individual characteristics ($\varphi_k(.)$) and time since treatment ($\delta_k(.)$). The simplest case is when $\delta_k(t - t_P)\varphi_k(x) = \exp(c_k)$.

The corresponding survival function is

$$S_U(t|t_P, P, x, v_U) = \exp\left(-\int_0^t h_U(s|t_P, P, x, v_U)ds\right)$$

For durations $t_U \leq t_P$ this is simply:

$$S_U(t|t \leq t_P, P = 0, x, v_U) = \exp\left(-\psi_U(x)v_U \int_0^t \theta_U(s)ds\right) \tag{17}$$

but when $t_U > t_P$ and treatment k has been received this is:

$$S_U(t|t_P, P = k, x, v_U) = \exp\left(-\psi_U(x)v_U\left(\int_0^{t_P} \theta_U(s)ds + \varphi_k(x)\int_{t_P}^t \theta_U(s)\delta_k(s - t_P)ds\right)\right)$$

If the assignment to treatment is considered exogenous, then this density is enough to estimate the model and evaluate the causal effects of the treatments. This would be the case if the unobserved terms v_1, v_2, v_3, v_4 were uncorrelated with v_U. However, when this is not true we have to model jointly the durations t_U and t_P as well as P. To do so, assignment to treatment is modeled in a competing risk framework. The hazard rates for unemployment duration until treatment k is received are:

$$h_k(t|x, v_k) = \theta_k(t)\psi_k(x)v_k, \quad k \in \{1, 2, 3, 4\} \tag{18}$$

The joint distribution of the duration to treatment and the received treatment is:

$$f(t, P|x, v) = \left[\prod_{k=1}^{4} h_k(t|x, v_k)^{1(P=k)}\right] \prod_{k=1}^{4} S_k(t|x, v_k) \tag{19}$$

where $S_k(t|x, v_k) = \exp\left(-\int_0^t h_k(s|x, v_k)ds\right)$. Notice finally that the probability that no treatment has been received up to a duration t is the product of the survival functions as they are (conditionally) independent:

$$P(t_P > t|x, v) = \prod_{k=1}^{4} S_k(t|x, v_k) \tag{20}$$

Let denote $c(U) = 1$ when the spell is not censored and $c(U) = 0$ when it is censored. The full density of endogenous observations $L(t_U, t_P, P|x, v)$ can be computed from the conditional and marginal densities $f(t_U|t_P, P, x, v)$ and $f(t_P, P|x, v)$, enabling us to compute the various contributions to the likelihood, accounting for censored durations:

$$\begin{aligned} L(t_U, t_P, P|x, v) &= \left[h_U(t_U|t_P, P, x, v_U) \prod_{k=1}^{4} h_k(t_P|x, v_k)^{1(P=k)}\right]^{c(U)} \times \\ & S_U(t_U|t_P, P, x, v_U) \prod_{k=1}^{4} S_k(t_P|x, v_k) \end{aligned} \tag{21}$$

The interest in specifying jointly the distribution of the unemployment duration and the duration until treatment is that they are endogenous in the sense that the assignment to treatment may depend on unobserved characteristics that are correlated with the unobserved terms entering the unemployment duration. To compute the joint distribution of endogenous variables conditional on the observables we have to integrate out of the unobserved terms. The likelihood is therefore:

$$L(t_U, t_P, P|x) = \int L(t_U, t_P, P|x, v)\, dG(v) \tag{22}$$

where $G(v)$ is the mixture distribution.

5.2 Including employment duration

In our data individuals enter, exit and sometime reenter unemployment. We consider as an employment spell a spell that begins with an exit from unemployment to employment. The duration of the spell is known when the individual reenters unemployment, otherwise the spell is treated as censored.

For individuals that exit from unemployment to employment, the likelihood involves an additional term which is the likelihood of the employment spell. It is treated as a duration model with hazard rate:

$$h_E(t|P,x,v_E) = \theta_E(t)\psi_E(x)v_E \prod_{k=1}^{4} [\gamma_k(x)]^{1(P=k)} \tag{23}$$

The effect of treatment k on employment duration is the function $\gamma_k(x)$, that may depend on covariates x. The additional term in the likelihood is therefore:

$$L_E(t_E, |P, x, v_E) = h_E(t|P,x,v_E)^{c(E)} \exp\left(-\int_0^t h_E(s|P,x,v_E)ds\right) \tag{24}$$

where $c(E) = 1$ when the spell is not censored and $c(E) = 0$ otherwise. The total likelihood is:

$$L(t_U, t_P, t_E, P|x, v) = L_E(t_E, |P, x, v_E)^{c(U)} L(t_U, t_P, P|x, v)$$

which is also integrated over the distribution of unobserved terms, enlarged to $v = (v_U, v_E, v_1, v_2, v_3, v_4)$. We conjecture that, in this part of the model, the joint distribution of unobserved heterogeneity and causal parameters are also identified (see Appendix 6).

5.3 Specification issues

5.3.1 Distribution of unobserved heterogeneity

We need to allow for correlations between durations that are not accounted for by observable characteristics. Therefore, when choosing the specification of the joint distribution of unobserved terms, we are interested in obtaining a covariance matrix as flexible as possible. However a completely flexible covariance matrix would not be feasible, as the number of parameters gets rapidly very large. We choose to model the distribution of the unobserved terms as a two-factor loading model: we assume that there are two unobserved factors V_1 and V_2 that enter every duration. The specification of the unobserved terms is thus:

$$v_k = \exp(\alpha_k^1 V1 + \alpha_k^2 V2) \tag{25}$$

Let Γ a 6×2 matrix formed by the coefficients α_k^1, α_k^2. The log-unobserved terms are therefore $w = \log(v) = \Gamma V$, with $V = (V_1, V_2)$. The covariance matrix of w is:

$$Var(w) = \Gamma Var(V) \Gamma' \tag{26}$$

Identification then requires some normalization. Clearly for any invertible matrix A : $Var(w) = \Gamma Var(V)\Gamma' = \Gamma A^{-1} A Var(V) A' A'^{-1} \Gamma'$. Thus, if Γ and $Var(V)$ are solutions, then ΓA^{-1} and $Var(AV)$ are also solutions. This problem can be avoided by assuming that the two underlying factors are uncorrelated ($Var(V) = I(2)$). However, this is not enough, because the covariance matrix of the unobserved terms is now

$Var\,(w) = \Gamma\Gamma'$, and for any 2×2 orthogonal matrix[4] Q, ΓQ is a solution. We thus impose a restriction on Γ, namely $\alpha_k^2 = 0$ for some k. Notice that some constraints are also needed on the mean of the unobserved terms as $E\,(w) = \Gamma E\,(V)$.

A frequent and natural choice is to model the unobserved factors as a discrete distribution with mass points, following Heckman and Singer (1984). Notice that strictly speaking it is not necessary to impose all the previous constraints in that case. However, choosing mass points is done in the aim of approximating any distribution function. We therefore impose normalization on the mean and the variance matrix of the two underlying factors. In addition to the above constraints, we impose two mass points for V_1 and for V_2, the lower and upper values being set to -1 and 1. We could want to impose other normalizations like zero mean and unit variance. However this would impose undesired important non linearities in the probabilities of the mass points. The case we examine is the simplest one in which there are only two mass points for each factors that take values -1 and 1.[5]

5.3.2 Duration dependance

Flexibility of the baseline hazard is limited by the practical difficulties in estimating the unobserved heterogeneity distribution (Baker and Melino, 2000). We adopt a piecewise constant hazard for the duration dependence functions $\theta_k(t)$, of the form:

$$\theta_k\,(t) = \sum_{l=1}^{l=L} \theta_{kl} 1\,(t \in I_l) \tag{27}$$

For unemployment duration, we allow for seven intervals, the first six of them being of equal length of 90 days, i.e. covering the first one and a half year of unemployment: $I_1 = [1, 90]\,,\ I_2 = [91, 180]\,,\ I_3 = [181, 270]\,,\ I_4 = [270, 360]\,,\ I_5 = [361, 450]\,,\ I_6 = [451, 540]\,,$ $I_7 = [541, 900[$. For all other durations, we set five intervals, the first four of them of 90 days $I_1 = [1, 90]\,,\ I_2 = [91, 180]\,,\ I_3 = [181, 270]\,,\ I_4 = [270, 360]\,, I_5 = [361, 900]$.

5.3.3 Practical implementation

Our dataset is very large, as it contains information on more than $500,000$ spells and we want to perform estimations including many covariates. Therefore it is not computationally possible to perform estimations over the whole sample. We could stratify the sample to make estimation on specific sub-populations, but we can also perform estimation on random subsamples. Yet, another problem is that more than 80% of the observations in the sample did not receive any treatment, thus only a small share of the sample contains information on the assignment to treatment and the effect of treatment. To overcome

[4] An orthogonal matrix satisfies $QQ' = I$

[5] We tried out alternative specifications: two-factor loading model with 3 points of support and three-factor loading model with 2 points of support. We also specified parametrically the distribution of unobserved heterogeneity by a normal distribution. In this case we impose $E\,(v) = 0$. However, these specifications yield much less precise parameter estimates than our chosen specification without improving the goodness-of-fit.

this problem, we sampled endogeneously, over-representing the treated individuals. We sampled about 10% of the original sample, but we included half the individuals that received a treatment and very few individuals with a truncated unemployment duration, because the latter bring little information about the time processes. Based on the Manski-Lerman (1977) approach, we maximized a weighed likelihood, where the weights are the inverse of the sample rates in each of the six strata (every treatment, observed exit and censored spells). The estimator is consistent and asymptotically normal but, as the objective is no longer a likelihood, we must use the robust variance estimator based on both the Hessian and the outer product of the gradient. Details are given in Appendix 7.

Because local maxima are likely, we run optimization a number of times with randomly chosen starting values. The tolerance for the gradient was set to 10^{-6} and we used Gauss maxlik procedure with the BFGS algorithm. Analytical gradients were used to speed-up optimization and to avoid imprecision in the Hessian computation. Out of, say, ten set of random starting values, most would converge to the same maximum, and a few would converge to another set of parameters with a lower likelihood. Having also checked the Hessian closely, we are thus confident that the reported estimates are at a global maximum.

6 Estimation results

Table 3 shows the estimated effects of the various counseling schemes in the model focusing on the transition rate from unemployment to work. This table reports the results in a model without unobserved heterogeneity (column 1) and the results allowing for correlated unobserved heterogeneity. In Table 4, we present the results of the various treatment effects in the full model, i.e. integrating both unemployment and employment durations. Again, the treatment effects are given in a model without and with unobserved heterogeneity. Finally, Table 5 contains the estimated effect of unemployment duration and individual characteristics on the transition rate from unemployment to work, from employment back to unemployment and to each of the counseling scheme.

INSERT TABLES 3, 4 AND 5 APPROXIMATELY HERE

First we concentrate the discussion of the results on the model integrating the duration of unemployment only. When unobserved heterogeneity is not allowed for, skill assessment and job search support have a positive and significant impact on the exit rate to work (see column1, Table 3). The largest effect is found for the job search support program which increases the exit rate by 48% ($= exp(0.39) - 1$) against 23% for skill assessment. On the other hand, project-orientated programs have no significant impact on the transition rate to work. Introducing correlated unobserved heterogeneity changes somewhat the evaluation results (see column 2, Table 3). The effect of the job search support program reinforces strongly. The transition rate is increased by nearly 100% for individuals attending this scheme. More importantly, the effect of skill assessment becomes not significant after controlling for selection on unobservables. Project-orientated programs have still no significant impact on the transition rate to work in the model with correlated unobserved heterogeneity.

The way the interest parameters has changed allowing for selection on unobservables is consistent with the estimated correlation between the unobserved characteristics in the employment and treatment processes (see column 2, Table 3). The correlation between the transition rate to employment and the transition rate to job search support is mildly negative (-0.15): unobserved characteristics decreasing the chance of finding a job also lead to higher chances of attending a job search support program. A neglect of this selection bias induces an under-estimation of the effect of this scheme in the model without unobserved heterogeneity (see column 1, Table 3). On the other hand, the correlation between the unobserved characteristics in the transitions to employment and skill assessment is strongly positive (0.41), indicating that individuals who are more likely to participate to this scheme are those with the most favourable (unobserved) characteristics. This can explain why the effect of this scheme becomes unsignificant when controlling for selection on unobservables. The (positive) correlations between transitions to employment and the project-orientated schemes are too weak to induce significant changes in the estimated effects of these programs. Note also that the correlations between the assignment rates to the various treatments is close to 1, indicating that the selection on unobservable attributes is quite similar in the different counseling programs. Finally, there is also selection on observables as shown in Table 5.

Introducing the employment duration in the model does not change the results regarding the treatment effects in the transition rate from unemployment to work (see Table 4). If we then look at the effects of counseling schemes on the exit rate from employment back to unemployment, we observe striking differences between the models allowing for selection on unobservables or not. In the model without unobserved heterogeneity, the effects of (skill and project) assessment schemes are not significantly different from 0. The effects of (job search and project) support schemes are significantly positive, indicating that participating to these programs raises the return rate to unemployment by about 15%. The conclusion is completely reversed when allowing for correlated unobserved heterogeneity. Apart from the skill assessment scheme which has still no significant effect on the return rate to unemployment, the treatment effects are all significantly negative in a similar magnitude. Participation to a counseling scheme helps to decrease the exit rate from work back to unemployment by 40% to 60% according to the scheme. This large change in the treatment effects between the two models results from a strong positive correlation (close to 1) between the transition rate from work to unemployment and the transition rates to the project assessment and the support-type schemes. Unobserved characteristics increasing the chance of leaving a job also lead to higher chances of attending these program.

These results are in accordance with the theoretical model of Section 3. Our findings point to a positive effect of the most intensive counseling scheme - job search support - both on the transition rate from unemployment to work and also on the subsequent employment duration. This provides evidence that if it is sufficiently intensive, counseling has an indirect effect on the reservation wage of the participant. Participating to a counseling scheme induces workers to be more selective concerning the productivity (and so the wage) of the job. Entering a more productive job in turn decreases the destruction rate of the job. The absence of effects for the skill assessment program was expected given its very short duration scheme (1 day to 80 hours max). The positive effect of project-orientated schemes on the employment duration and their absence of effect on the unemployment duration is more troublesome. As we will see it below, there is however evidence that the effect of project-orientated schemes on the exit rate to work becomes positive three months after the start of the program.

We perform some sensitivity analysis with respect to the model specification of the treatment effects. First, we allow the effect of the schemes to vary over some selected characteristics in the unemployment and employment duration. The results of this specification are shown in Table 6. We report the treatment effects for various groups of unemployed workers defined according to the level of signifiance of the parameter estimates. In the unemployment duration, the effects differ significantly according to the age group (< or >=30 years old), the education level (< or >= secondary schooling) and the recent unemployment experience (short-term cumulative unemployment duration). Note that the effect of job search support. (but not the other programs) is also significantly lower (of about 0.2) for workers not receiving unemployment benefits.

INSERT TABLE 6 APPROXIMATELY HERE

From Table 6, we can conclude that the effects of skill and project assessment schemes on the transition to work are not significantly different from 0 whatever the (observed) characteristics of the unemployed workers. For the support-type schemes, the effects are heterogeneous across groups of unemployed people. The effect of job search support on the exit rate to employment is significantly positive except for young unemployed workers with no schooling degree. For the other groups of workers, the effect is the highest for the prime-aged educated workers. Their uneducated counterparts benefit much less for the scheme. At the aggregate level, the unemployed workers do not benefit from the project support scheme. When looking at different types of workers, we notice that the exit rate to work of those with no schooling degree is even negatively affected by participating to the scheme. For uneducated unemployed persons, the fact of defining a new employment project is harmful to the chances of finding rapidly a new job. We cannot of course exclude that participating to this type of scheme increases the enrolment to training schemes and eventually, raises the exit rate to work. Finally, treatment effects vary according to the date of entry into unemployment. For all schemes, the treatment effects are lower for the unemployed workers entered at the end of the period (September 2003) that for those entered at the date of the reform (July 2001). However, the difference is significant only for the job-search support scheme. This finding can be driven by several factors. The rise in the number of participants since the launch of the PAP in July 2001 could reduce the beneficial effect of the schemes in a context of heterogeneous treatment effects. This could also reflect a maturation effect (see Blundell *et al.*, 2004): the case workers involved in the project are less enthusiastic two years after the launch of the program than initially. Finally, the effect of counseling schemes can be sensitive to the state of the labour market, decreasing in a recession. We would need additional explanatory variables to disentangle between these different effects.

Secondly, the effect of the various schemes is assumed to vary with elapsed duration since the start of the scheme. We allow the effect after the completion of the program to differ from the effect during the period of participation. The latter is assumed to span three months (the maximum duration of the schemes analysed). In Table 6, we report the estimated effects of the various PAP schemes allowing for time dependence in the effects. If the incremental effect '$>$ 3 months' is positive and significant, this means that the effect after the completion of the program is higher than the effect during the period of participation. This is the case for all schemes except for skill assessment. The most striking result is for the project-orientated schemes (assistance and support). During the first three months of participation, participation to these programs does not raise the exit rate from unemployment. Thereafter, the exit rate jumps significantly by about 70% for project assessment and 30% for project support. This is consistent with some locking-in effect. Project-orientated programs aim to identify the skills of the unemployed person and match them with a new employment project compatible with the state of the labor market. This stage can therefore not result in a higher arrival rate of job offers. It is only on completing the scheme that the case worker in charge of the program may help the individual to foster the search of jobs corresponding with his/her new employment project. Note that the incremental increase after three months is not sufficient to compensate the negative effect estimated for some groups of unemployed persons (for instance the uneducated workers receiving a project support scheme). A differential time effect is also found significant for the job-search support scheme, although in a less extent. During the first three months of participation, the exit rate from unemployment to work increases by more than 90%. Thereafter, the exit rate has an additional jump of 15%.

We end this section by discussing the estimated effect of unemployment duration on the transition rate from unemployment to work, from employment back to unemployment and to each of the counseling scheme. Figure 3 describes the estimated duration dependence in the hazards into the schemes. As in the empirical hazards rate (see Figure 1), we observe peaks related to compulsory interviews at 0, 6 and 12 months. We also notice that the assignment rate to job-search support is higher for long-term unemployed people, while the assignment rate to the other schemes remains roughly constant over the duration of unemployment. Figure 4 displays the estimated duration dependence in the hazard rates of exits to employment and unemployment. The unemployment-employment (U-E) transition exhibits a non-monotonic true duration dependence, constant over the first 9 months of unemployment then decreasing. There is a 30% decrease in the hazard after one year of unemployment. The employment-unemployment (E-U) transition exhibits a U-shape pattern, first increasing over the first 9 months of unemployment and then deceasing. After 12 months of employment, the hazard rate has dropped by 40%. The same pattern is found for the employment-unemployment (E-U) transition, with peaks at 6 and 12 months that may be related to standard contract durations.

INSERT FIGURES 3 AND 4 APPROXIMATELY HERE

7 Interpreting the results using the parameters of the evaluation literature

The parameters presented above are difficult to interpret directly because the effect on exit rates depends on the baseline value of the hazard function and, when heterogeneous effects are considered, on the distribution of covariates. We consider various measures of the effect of the scheme by way of simulations.

First we concentrate on exit rates from unemployment. We measure the effect of the policy as changes in the survival function at different points in time for the populations of individual that receive a given treatment. These measures are close to the measures used in the evaluation literature known as treatment effect on the treated. We consider a large set of time periods and measure the change in the exit rate at the end of each period due to participation in a scheme during that period. More precisely, let β_P be the coefficient vector of the treatment effects. We consider the probability of having found a job at a given date t implied by the assignment to treatment before t and compare this with the probability of having found a job for the same assignment to treatment when effects are set to zero (i.e.$\beta_P = 0$). For treatment k, this is:

$$c(k,t) = P\left(t_E < t | \beta_P = \widehat{\beta}_P, t_k < t, P = k\right) - P\left(t_E < t | \beta_P = 0, t_k < t, P = k\right) \quad (28)$$

We also want to measure the change in the aggregate exit rate of unemployment. Indeed, whereas the previous measure concentrates on the treated, we also would like to take into account the presence of non-treated individuals. This measures the effect of the treatment as well as the intensity of assignment to the treatment:

$$\begin{aligned} c(t) &= P\left(t_E < t | \beta_P = \widehat{\beta}_P\right) - P\left(t_E < t | \beta_P = 0\right) \\ &= \sum_k \left[P\left(t_E < t | \beta_P = \widehat{\beta}_P, t_k < t, P = k\right) - P\left(t_E < t | \beta_P = 0, t_k < t, P = k\right)\right] \\ &\quad \times P\left(t_k < t, P = k\right) + 0 \times P\left(t_k \geq t\right) \\ &= \sum_k c(k,t)\, P\left(t_k < t, P = k\right) \end{aligned} \quad (29)$$

Similar computations can be performed on the employment duration.

To measure all these parameters, rather then computing an exact expression which is complicated, we simulate the model. We first draw a random term in the distribution of unobserved heterogeneity for each individual in the sample. This allows us to compute the quantities $\psi_U(x)v_U$, $\psi_E(x)v_E$, $\psi_k(x)v_k$, $k = 1, \ldots, 4$. We then draw four independent values for the duration upon each treatment, i.e. draws in the distribution of t_1 to t_4 conditional on x and v. To this aim, we draw four independent values in a uniform distribution on $[0,1]$: u_1 to u_4. We then compute a corresponding duration, solving $F_k(t) = u_k$. As the survival function is $S_k(x,t) = exp\left(-\psi_k(x)v_k \int_0^t \theta_k(s)\,ds\right)$. This is simply the solution of $\int_0^t \theta_k(s)\,ds = \ln(1-u_k)/\psi_k(x)v_k$, which is easy to solve given the piecewise constant expression of the duration dependence. The duration to potential treatment and treatment are defined by $t_P = \min(t_1, t_2, t_3, t_4)$ and $P = \arg\min(t_1, t_2, t_3, t_4)$. Once this duration to potential treatment is drawn, we draw in the distribution of t_E conditional on x, v_E and t_P. This is performed along the same lines : we draw a random number in the uniform distribution and solve $\int_0^t \theta_E(s, t_T)\, ds = \ln(1 - u_E) / \psi_E(x) v_E$. The only difference is that the duration dependence now depends on the duration to potential treatment. Once this duration is drawn, we can define the duration to treatment which is censored if $t_E < t_P$. Simulations in the employment duration is performed in a similar way.

In order to account for the precision of the estimators, we make this simulation for a number of draws into the normal distribution of parameters, using the estimated variance-covariance. Therefore, there are two sources of variability: one is the variance of the estimator and the other is the variance of the distribution of durations conditional on x and a vector of parameters. The confidence interval in the figures account for those two sources.

The results of these simulations are the following. Despite the effectiveness of the policy, the low number of individuals who benefited from it leads to small aggregated impacts (see Figures 5a and 5b). The proportion that have found a job after 900 days increases by only 0.5 percentage points, which is not large. The aggregate effect on the probability of remaining employed is larger and significant. The proportion that have left employment after 900 days decreases by 5 percentage points.

INSERT FIGURES 5a AND 5b APPROXIMATELY HERE

The effect of the four counseling programs on the transition rates of the treated individuals are given in Figures 6a to 8b. Only participation to job-search support increases the chances of leaving unemployment. After 900 days, the proportion of workers that have participated to job-search support and exited from unemployment to employment has raised by nearly 10 percentage points as compared to non-participation. Apart from skill assistance, other counseling schemes reduce the proportion of their participants that have left employment after 900 days by 12% to 26% points according to the type of scheme.

INSERT FIGURES 6a, 6b, 7a, 7b, 8a AND 8b APPROXIMATELY HERE

8 Conclusion

This paper evaluates the causal effects of job-search assistance schemes that became central in the public unemployment services since the July 2001 reform in France. Although this is only one dimension of the reform, it is a major innovation in the national context, with substantial budgetary effort, and one that lacks systematic evaluation. The theoretical analysis of this type of intervention predicts that, provided it increases the arrival rate of job offers, it should both decrease unemployment duration and lower unemployment recurrence.

The available database makes possible estimation of those effects using identification results that rely only on duration information. Because the data is large, we can exploit all the flexibility that is available within this class of models, making the effects of the treatment depend on elapsed time and observed individual characteristics, even for a large number of potential treatments.

Generally, all schemes considered are found to have some impact on both unemployment and employment duration, except for the basic skill assessment program. The job-search support program has the strongest effect which acts directly from the start of effective treatment. In contrast, there is a lock-in effect of the "project" schemes that is consistent with their design. Heterogeneity of the effects is present in some instances and the efficiency of the schemes decreases with time, to which the cycle probably contributes.

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Table 1: Sample statistics

Total number of spells	516 821
Of which exit to employment	192 876
Number of individuals	404 302
Number of spells with some treatment	86 253
Number of spells with 1 treatment	68 980
Number of spells with 2 treatments	14 194
Number of spells with more than 2 treatments	3 079
Among spells with 1 treatment:	
Skill assessment	10 423
Project assessment	10 060
Job-search support	30 310
Project support	18 187

Source: FHS-ANPE, authors computation. Excluding unknown destination.

Table 2: Sample statistics of spells

	Spells with no treatment	Skill assessment	Project assessment	Job-search support	Project support
Female	52.9%	56.6%	61.5%	57.5%	60.9%
Male	47.1%	43.4%	38.5%	42.5%	39.1%
French	89.8%	88.4%	94.6%	89.2%	90.5%
Not French	10.2%	11.6%	5.4%	10.8%	9.5%
Children	36.7%	48.6%	46.6%	42.8%	39.3%
No children	63.3%	51.4%	53.4%	57.2%	60.7%
Married	39.6%	49.5%	47.9%	43.5%	38.8%
Not maried	60.4%	50.5%	52.1%	56.5%	61.2%
RMI	8.6%	10.2%	7.6%	14.0%	11.8%
UB	68.4%	75.9%	79.5%	71.1%	67.1%
Neither	23.1%	13.9%	12.9%	14.8%	21.1%
Higher education	23.3%	21.3%	40.9%	24.2%	22.3%
Bac	19.4%	22.9%	24.1%	16.0%	22.2%
Secondary	43.4%	46.4%	31.6%	44.7%	46.9%
Elementary school	13.8%	9.4%	3.4%	15.1%	8.6%
Age in years	32.3	34.7	35.5	35.4	32.3

Source: FHS-ANPE, authors computation. Spells with no or one treatment. Excluding unknown destination.

Table 3: Estimates of treatment effects in the unemployment duration model

	Without UH		With UH	
	coeff.	sd	coeff.	sd
Treatment effects				
Skill assessment	**0.21**	0.04	0.10	0.16
Project assessment	0.00	0.04	0.02	0.13
Job-search support	**0.39**	0.03	**0.69**	0.07
Project support	-0.05	0.03	-0.13	0.10
Factor loading				
Unemployment - Employment (U-E)				
constant (θ1)	**-6.54**	0.12	**-7.46**	0.19
γ1			**-0.22**	0.08
γ2			**1.11**	0.09
Skill assessment	**-9.69**	0.18		
constant (θ1)			**-9.51**	0.25
γ1			0.43	0.36
γ2			0.21	0.17
Project assessment				
constant (θ1)	**-11.01**	0.21	**-11.35**	0.30
γ1			**1.78**	0.15
γ2			0.33	0.19
Job-search support				
constant (θ1)	**-7.82**	0.15	**-7.60**	0.26
γ1			**1.22**	0.17
γ2			0.00	
Project support				
constant (θ1)	**-7.95**	0.15	**-7.80**	0.23
γ1			**1.13**	0.15
γ2			**0.30**	0.14
Probabilities				
prob(V1=-1)			**0.84**	0.04
prob(V1=1)			**0.16**	
prob(V2=-1)			**0.40**	0.04
prob(V2=1)			**0.60**	
Correlation between				
U-E and skill ass.			0.41	
U-E and project ass.			0.09	
U-E and job search supp.			-0.15	
U-E and project supp.			0.18	
Skill ass. and project ass.			0.95	
Skill ass. and job search supp.			0.84	
Skill ass. and project supp.			0.97	
Project ass. and job search supp.			0.97	
Project ass. and project supp.			1.00	
Job-search supp. and project supp.			0.94	
Mean log Likelihood weighted	-4.0799183		-4.0759334	
# parameters	191		202	
# observations	51 894		51 894	

Note: In bold, estimates not significantly different from zero at 5%.

Table 4: Estimates of treatment effects in the full model

	Without UH		With UH	
	coeff.	sd	coeff.	sd
Treatment effects: Unemployment - Employment				
Skill assessment	**0.22**	0.04	0.12	0.18
Project assessment	0.01	0.04	-0.12	0.13
Job-search support	**0.41**	0.03	**0.59**	0.06
Project support	-0.03	0.03	-0.15	0.12
Treatment effects: Employment - Unemployment				
Skill assessment	-0.03	0.06	0.08	0.21
Project assessment	0.07	0.06	**-0.86**	0.15
Job-search support	**0.11**	0.03	**-0.64**	0.15
Project support	**0.16**	0.04	**-0.51**	0.13
Factor loading				
Unemployment - Employment (U-E)				
constant (θ1)	**-6.63**	0.12	**-7.43**	0.19
γ1			-0.08	0.05
γ2			**1.08**	0.10
Employment - Unemployment (E-U)				
constant (θ1)	**-7.11**	0.08	**-6.95**	0.15
γ1			**0.64**	0.10
γ2			0.12	0.09
Skill assessment				
constant (θ1)	**-9.74**	0.18	**-10.04**	0.73
γ1			-0.39	0.87
γ2			**0.13**	0.19
Project assessment				
constant (θ1)	**-10.96**	0.20	**-11.55**	0.38
γ1			1.82	0.23
γ2			**0.28**	0.19
Job-search support				
constant (θ1)	**-7.89**	0.15	**-7.89**	0.26
γ1			**1.30**	0.16
γ2			0.00	
Project support				
constant (θ1)	**-7.98**	0.15	**-7.95**	0.23
γ1			**1.11**	0.21
γ2			**0.22**	0.15
Probabilities				
prob(V1=-1)			**0.78**	0.05
prob(V1=1)			**0.22**	
prob(V2=-1)			**0.41**	0.04
prob(V2=1)			**0.59**	
Correlation between				
U-E and skill ass.			0.43	
U-E and project ass.			0.12	
U-E and job search supp.			-0.06	
U-E and project supp.			0.17	
Skill ass. and project ass.			-0.84	
Skill ass. and job search supp.			-0.93	
Skill ass. and project supp.			-0.82	
Project ass. and job search supp.			0.98	
Project ass. and project supp.			1.00	
Job-search supp. and project supp.			0.97	
U-E and E-U			0.16	
E-U and skill ass.			-0.82	
E-U and project ass.			1.00	
E-U and job search supp.			0.98	
E-U and project supp.			1.00	
Mean log Likelihood weighted	-5.2399254			
# parameters	232		245	
# observations	51 894		51 894	

Note: In bold, estimates not significantly different from zero at 5%.

Table 5: Estimated effect of duration and individual characteristics on the transition rates
Full model

	U-E		Skill ass.		Project ass.		Job-search supp.		Project supp.		E-U	
	coeff.	sd	coeff.	sd	coeff.	sd	coeff.	sd	coeff.	sd	coeff.	sd
Duration dependence (< 3 months)												
3-6 months	-0.05	0.03	**-0.41**	0.06	**-0.74**	0.07	**-0.34**	0.04	**-0.57**	0.04	**0.30**	0.04
6-9 months	-0.04	0.04	**-0.17**	0.08	-0.07	0.10	**0.35**	0.05	**-0.14**	0.06	**0.26**	0.06
9-12 months	**-0.31**	0.05	**-0.38**	0.11	**-0.38**	0.14	0.09	0.08	**-0.44**	0.09	0.01	0.07
12-15 months (col. 1) or > 12 months (col. 2-6)	**-0.32**	0.06	**-0.37**	0.14	0.07	0.19	**0.36**	0.12	-0.25	0.13	**-0.50**	0.09
15-18 months	**-0.44**	0.08										
> 18 months	**-0.50**	0.09										
Personal characteristics												
male	**0.22**	0.04	-0.08	0.05	**-0.46**	0.06	**-0.21**	0.05	**-0.32**	0.05	**-0.06**	0.02
no children	0.05	0.05	**-0.14**	0.06	0.00	0.07	-0.03	0.06	-0.03	0.06	**0.07**	0.03
not French	**-0.44**	0.07	**0.25**	0.09	**-0.46**	0.11	**0.28**	0.08	0.05	0.08	**0.32**	0.05
married	0.02	0.05	**0.14**	0.06	-0.01	0.07	-0.04	0.06	**-0.14**	0.06	**-0.09**	0.03
Education (elementary school)												
secondary	-0.11	0.06	**0.40**	0.07	**0.74**	0.09	-0.02	0.07	**0.21**	0.07	0.04	0.03
bac	-0.05	0.07	**0.51**	0.09	**1.36**	0.10	-0.11	0.08	**0.17**	0.08	-0.07	0.04
higher education	**0.12**	0.06	0.14	0.09	**1.52**	0.10	**0.23**	0.08	-0.03	0.08	**-0.40**	0.04
Age (below 25 years)												
25 to 30 years	**-0.30**	0.06	0.08	0.08	**0.73**	0.10	**-0.37**	0.07	**-0.15**	0.07	**-0.14**	0.04
30 to 40 years	**-0.34**	0.06	0.11	0.08	**1.06**	0.10	**-0.29**	0.08	-0.14	0.07	0.00	0.04
40 to 50 years	**-0.32**	0.07	**0.25**	0.09	**1.22**	0.11	**0.17**	0.08	-0.04	0.08	0.06	0.04
50 to 55 years	**-0.22**	0.10	0.07	0.13	**1.02**	0.16	**0.22**	0.12	**-0.42**	0.13	0.09	0.07
Region of residence (Paris)												
R1 (high unemployment rate)	-0.01	0.06	0.06	0.08	0.16	0.08	**0.38**	0.07	0.03	0.07	**0.35**	0.04
R2 (medium unemployment rate)	**0.24**	0.06	0.03	0.08	0.07	0.09	**0.41**	0.08	0.13	0.07	**0.34**	0.04
R3 (low unemployment rate)	**0.36**	0.06	0.06	0.08	**0.17**	0.09	**0.33**	0.07	**0.18**	0.07	**0.40**	0.04
Reason of entry into unemployment (first entry)												
firing	**0.18**	0.08	0.12	0.12	**0.50**	0.13	**-0.32**	0.11	**-0.21**	0.10	**-0.25**	0.06
demission	**0.56**	0.09	0.22	0.14	**0.49**	0.15	**-0.21**	0.12	-0.15	0.12	-0.08	0.06
end of contract	**0.66**	0.08	-0.07	0.11	0.11	0.12	**-0.45**	0.10	**-0.42**	0.09	0.08	0.05
others	0.12	0.08	0.15	0.11	**0.29**	0.12	**-0.20**	0.10	-0.17	0.09	-0.07	0.05
Unemployment experience (duration=0)												
log(long-term cumulative duration)	0.00	0.02	-0.02	0.03	-0.02	0.03	-0.04	0.03	-0.04	0.03	**0.04**	0.01
log(short-term cumulative duration)	**-0.79**	0.07	**-0.22**	0.09	**-0.57**	0.11	-0.06	0.09	**-0.43**	0.09	0.05	0.04
Short-term unemployment recurrence (0 spell)												
1 spell	**1.30**	0.13	**0.35**	0.17	**0.59**	0.20	-0.09	0.17	**0.45**	0.16	**0.07**	0.08
2 spells	**1.51**	0.15	**0.46**	0.20	**0.67**	0.23	-0.01	0.19	**0.48**	0.18	**0.14**	0.09
> 2 spells	**1.85**	0.15	**0.53**	0.21	**0.77**	0.24	0.09	0.20	**0.55**	0.19	**0.43**	0.09
Cohort effect (July 2001=1)												
log(date of entry into unemployment)	**-0.11**	0.03	**0.23**	0.04	**0.27**	0.05	**0.24**	0.04	**0.23**	0.04	**0.08**	0.02
log(date of entry into unemployment)^2	**-0.07**	0.02	**-0.04**	0.02	**-0.15**	0.03	**-0.06**	0.02	**-0.04**	0.02	0.00	0.01
Social transfers (no rmi)												
rmi	**-0.92**	0.07	-0.11	0.09	**-0.39**	0.14	**0.31**	0.08	0.09	0.08	-0.02	0.05
Unemployment benefits (no UB)												
UB - 122 days	**-0.64**	0.08	**-0.46**	0.13	**-0.35**	0.12	**-0.35**	0.11	**-0.54**	0.11	**0.19**	0.05
UB - 213 days	**-0.72**	0.07	-0.19	0.10	-0.16	0.12	**-0.23**	0.09	**-0.46**	0.09	**0.18**	0.04
UB - 456 days	**-0.62**	0.07	-0.09	0.11	**0.25**	0.12	0.04	0.09	**-0.31**	0.09	**0.14**	0.04
UB - 700 days	**-1.04**	0.08	0.20	0.11	0.07	0.09	0.15	0.10	-0.08	0.10	**0.19**	0.07
UB - 912 days	**-0.82**	0.06	0.02	0.09	-0.02	0.19	0.07	0.08	**-0.26**	0.07	-0.03	0.03
UB - > 50 years	**-1.78**	0.13	-0.18	0.17			0.04	0.15	**-0.57**	0.16	-0.02	0.11
# parameters	245											
# observations	51 894											

Note: In brackets, reference category. In bold, estimates not significantly different from zero at 5%.

Table 6: Heterogeneous treatment effects in the full model

	Skill ass.		Project ass.		Job-search supp.		Project supp.		# param.
	coef.	sd	coef.	sd	coef.	sd	coef.	sd	
Unemployment duration									
Constant effect	0.12	0.18	-0.12	0.13	**0.59**	0.06	-0.15	0.12	245
Effect dependent on elapsed duration since the start of the scheme*									
short-term effect: 0-3 months	0.00	0.15	-0.04	0.22	**0.66**	0.29	-0.05	0.13	234
incremental effect: > 3 months	-0.01	0.08	**0.53**	0.15	**0.14**	0.07	**0.24**	0.11	
Effect dependent on selected individual characetristics**									
>=30, educated, short unemployment experience	-0.09	0.18	-0.13	0.15	**0.64**	0.08	-0.16	0.14	293
>=30, educated, long unemployment experience	0.14	0.18	-0.15	0.15	**0.72**	0.08	0.02	0.14	
>=30, uneducated, short unemployment experience	-0.08	0.20	-0.32	0.21	**0.20**	0.09	**-0.53**	0.16	
>=30, uneducated, long unemployment experience	0.15	0.20	-0.34	0.21	**0.29**	0.09	**-0.35**	0.16	
<30, educated, short unemployment experience	0.00	0.19	0.05	0.16	**0.49**	0.08	-0.18	0.14	
<30, educated, long unemployment experience	0.23	0.19	0.03	0.16	**0.57**	0.08	0.00	0.14	
<30, uneducated, short unemployment experience	0.00	0.22	-0.13	0.23	0.05	0.10	**-0.55**	0.16	
<30, uneducated, long unemployment experience	0.24	0.22	-0.16	0.23	0.14	0.10	**-0.38**	0.16	
Effect dependent on the date of entry into unemployment***									293
juil-01	**0.80**	0.37	0.20	0.37	**1.38**	0.22	0.47	0.30	
sept-03	-0.03	0.18	**-0.37**	0.16	**0.51**	0.09	**-0.34**	0.14	
Employment duration									
Constant effect	0.08	0.21	**-0.86**	0.15	**-0.64**	0.15	**-0.51**	0.13	245
Effect dependent on selected individual characetristics****									293
educated	0.09	0.18	**-0.88**	0.17	**-0.75**	0.16	**-0.62**	0.16	
uneducated	-0.11	0.25	-0.40	0.26	**-0.59**	0.16	**-0.61**	0.19	

Note: In bold, estimates not significantly different from zero at 5%.

* Short-term effect for a reference individual: >=30, educated, mean unemployment experience, female and receiving UB.

** Since the treatment effects vary according to the date of entry into unemployment, we report the effects in the cohort entered in the middle of the observation period. Apart from the date of entry into unemployment, the effects differ only significantly according to the age group, the education level and the recent unemployment experience (short-term cumulative unemployment duration).

*** Effect for a reference individual: >=30, educated, mean unemployment experience, female and receiving UB.

**** The effects differ significantly according to the education level. Note that the effect of job-search support (but not the other programs) is also significantly lower (of about 0.2) for workers not receiving unemployment benefits.

Figure 1: Schemes empirical duration dependence

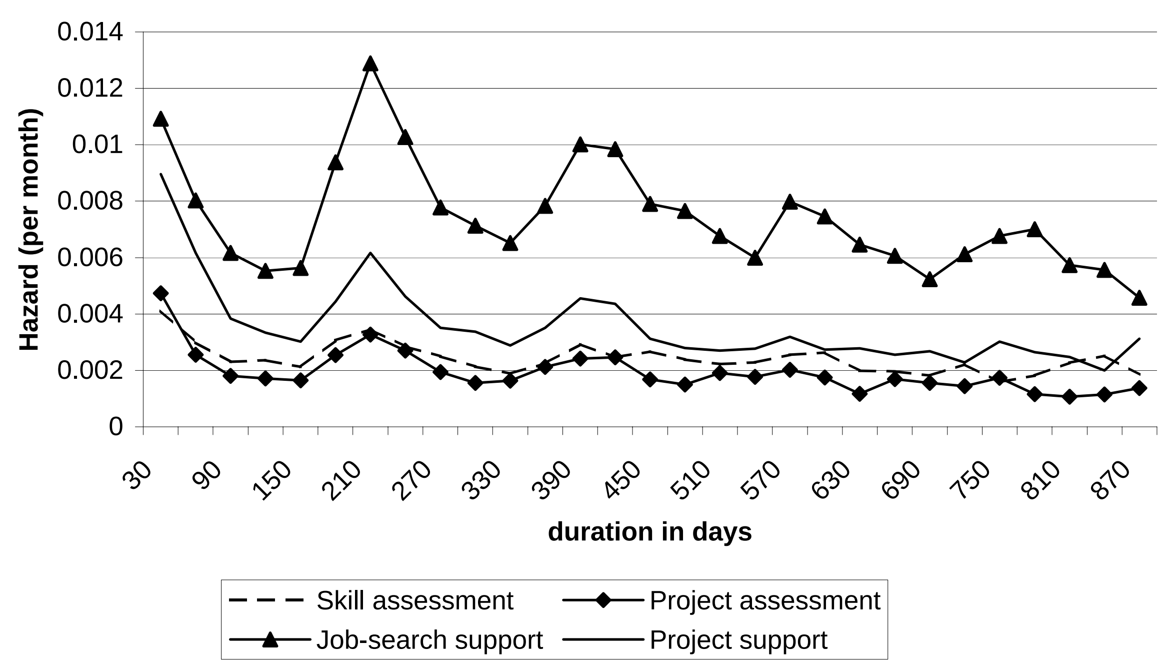


Figure 2: Unemployment and employment empirical duration dependence

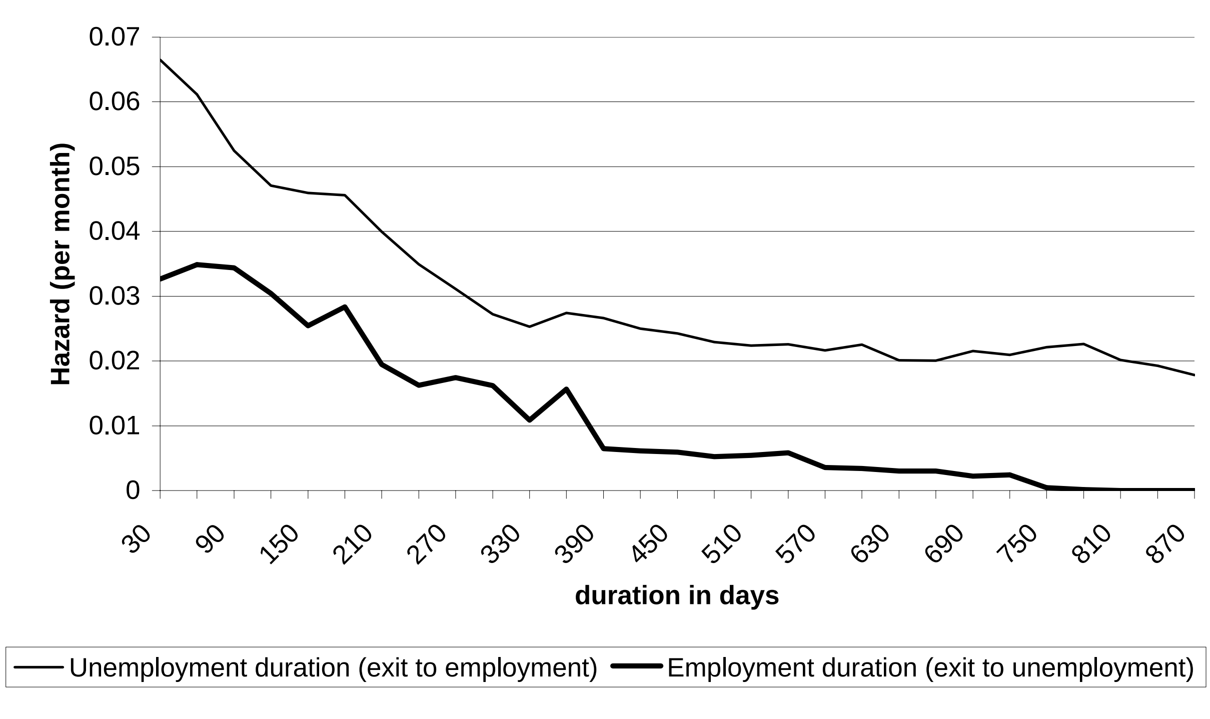


Figure 3: Schemes estimated duration dependence

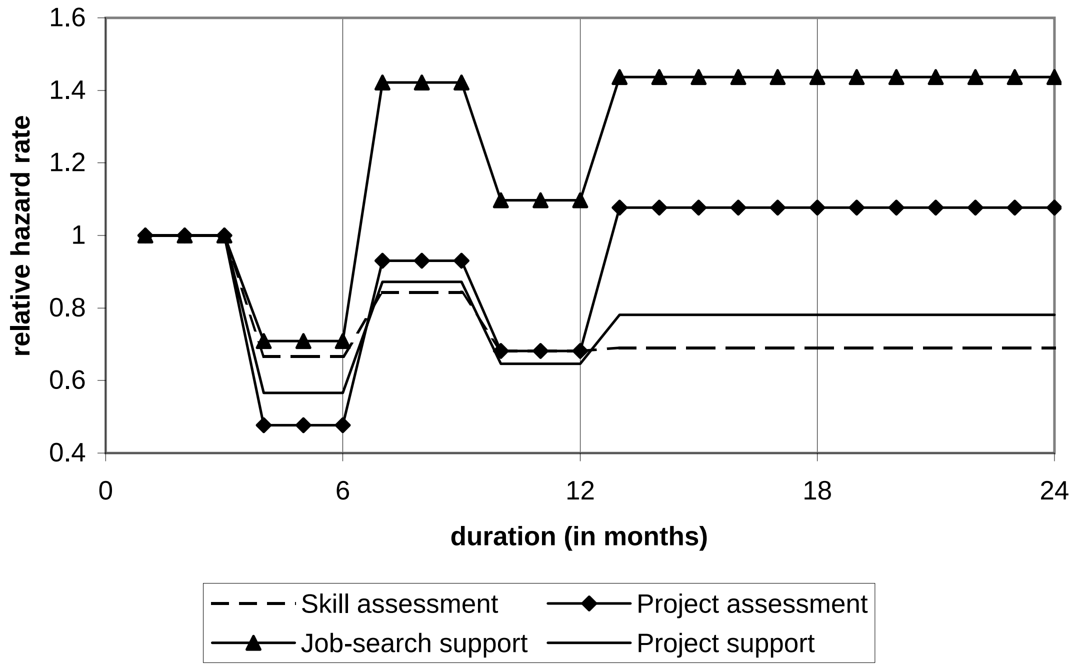
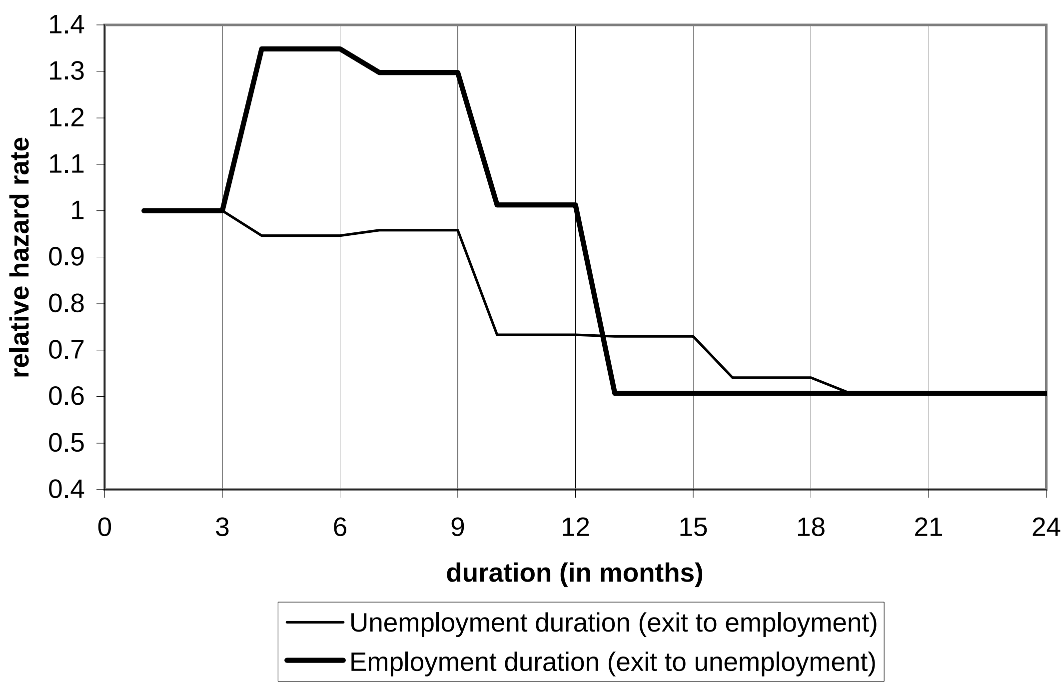


Figure 4: Unemployment and employment estimated duration dependence



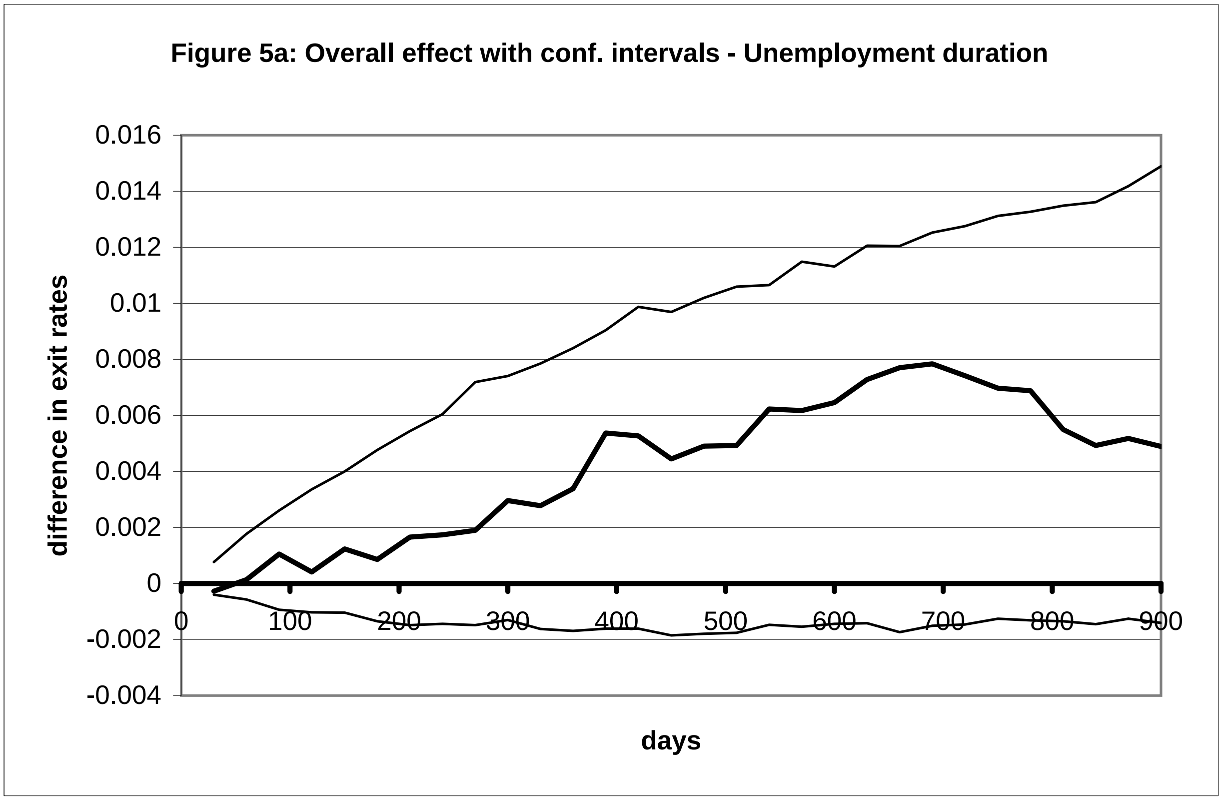


Figure 5a: Overall effect with conf. intervals - Unemployment duration
0.016
0.014
0.012
0.01
0.008
0.006
0.004
0.002
0
-0.002
-0.004
difference in exit rates
0
100
200
300
400
500
600
700
800
900
days

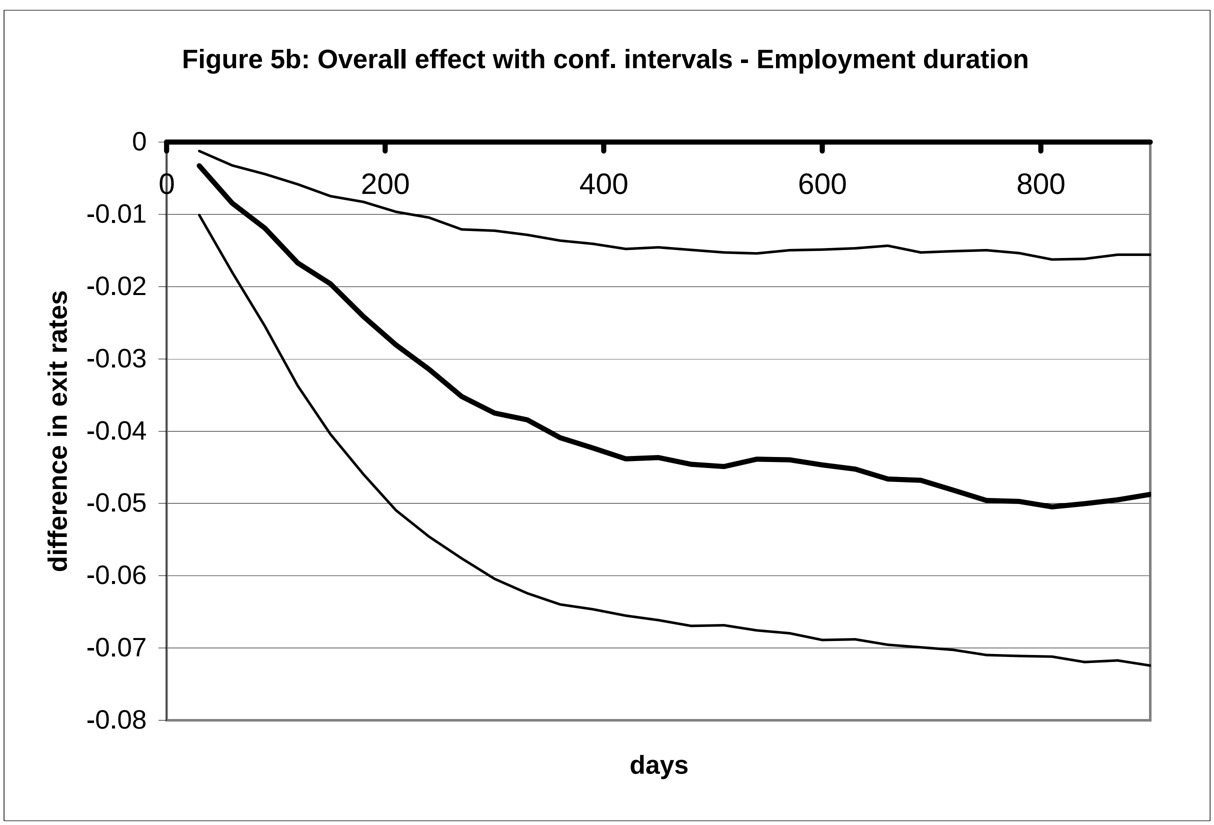


Figure 5b: Overall effect with conf. intervals - Employment duration
0
-0.01
-0.02
-0.03
-0.04
-0.05
-0.06
-0.07
-0.08
difference in exit rates
0
200
400
600
800
days

Figure 6a: Effect of skill assessment on the treated with conf. int. - Unemployment duration

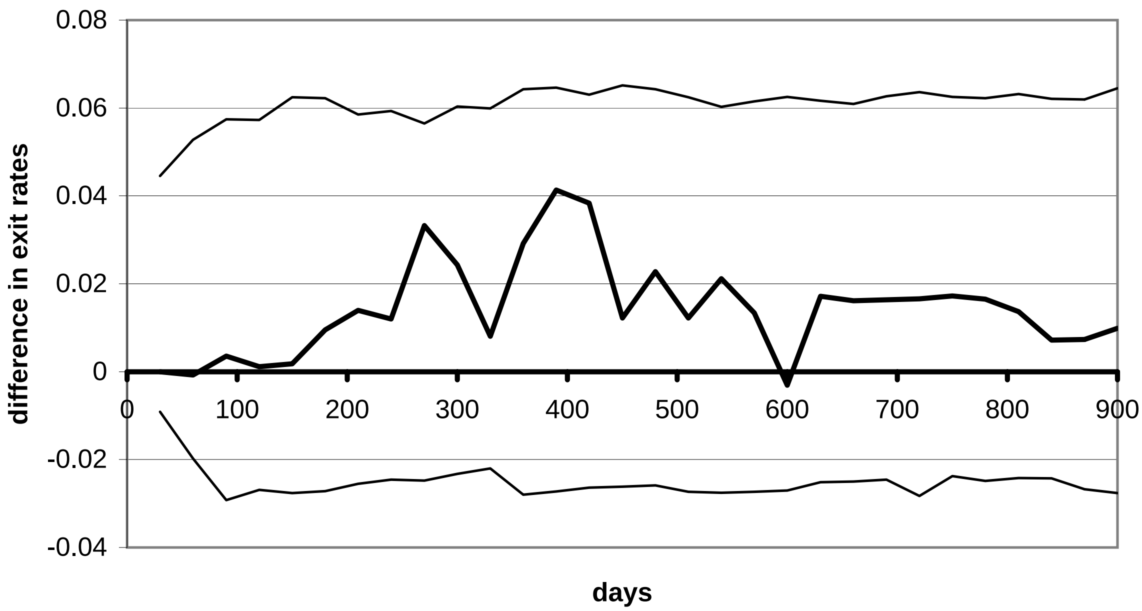


Figure 6b: Effect of skill assessment on the treated with conf. int. - Employment duration

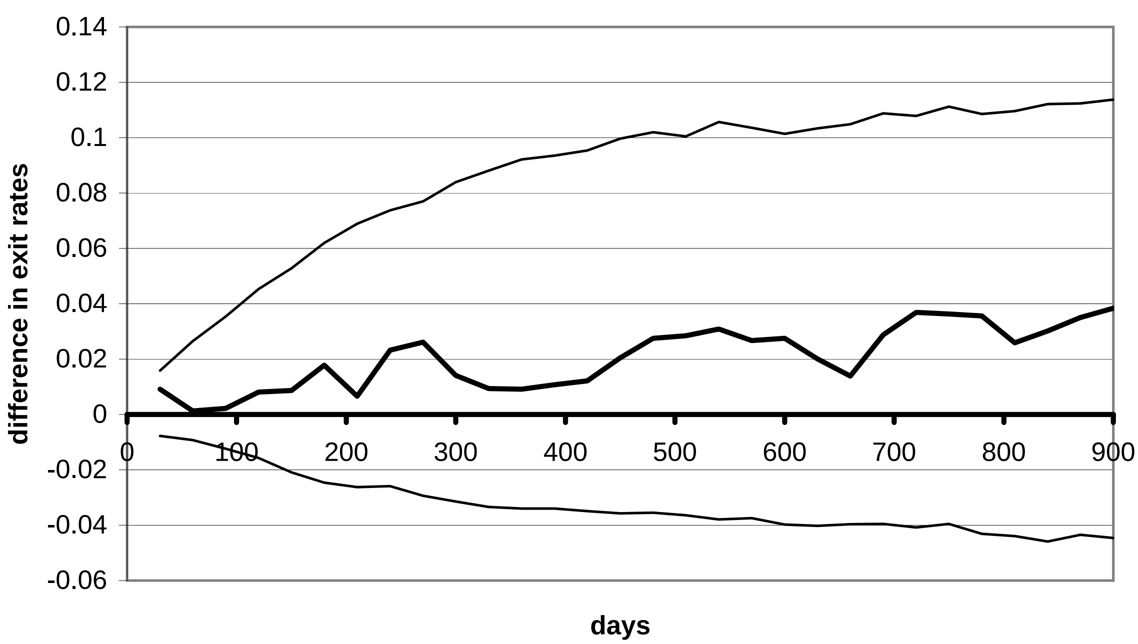


Figure 7a: Effect of project assessment on the treated with conf. int. - Unemployment duration

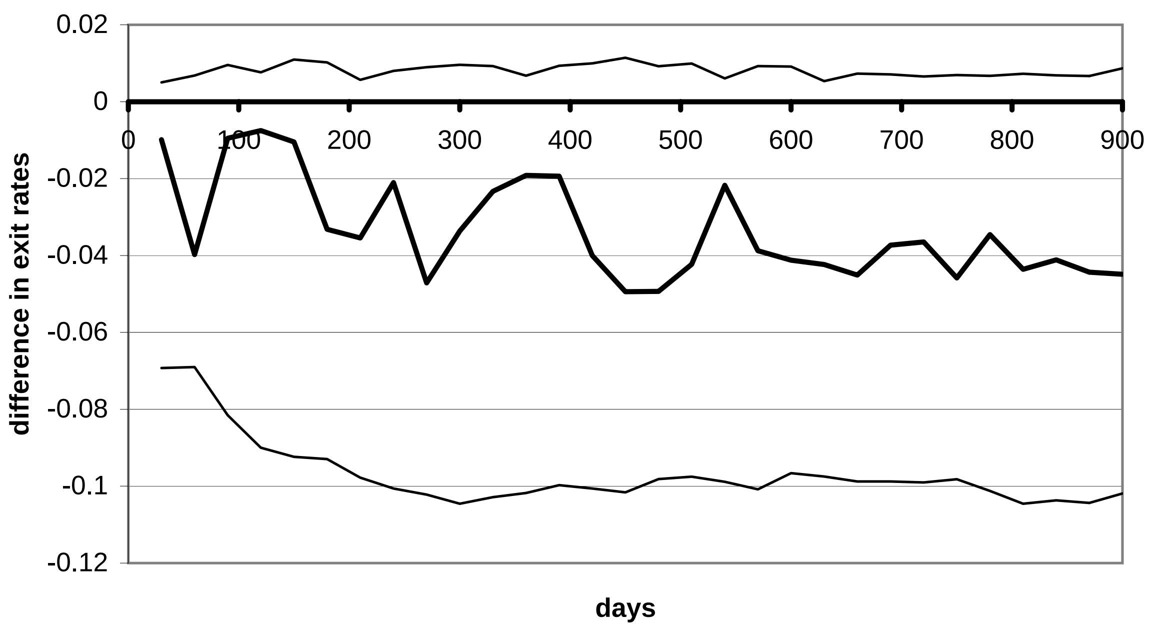


Figure 7b: Effect of project assessment on the treated with conf. int. - Employment duration

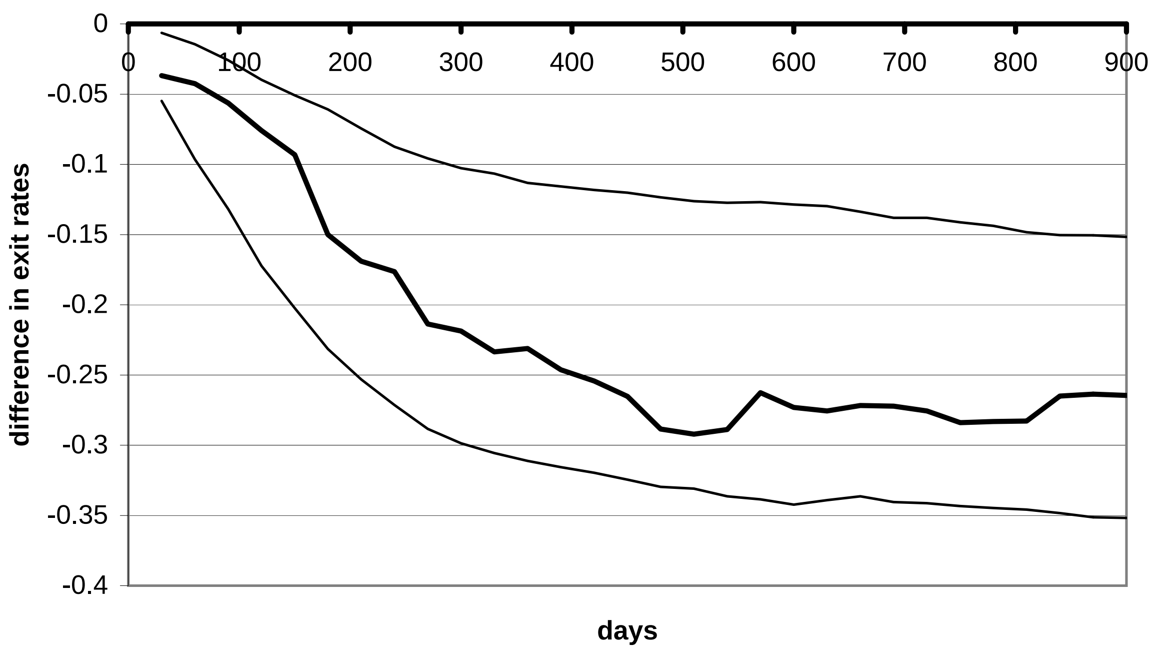


Figure 8a: Effect of job-search support on the treated with conf. int. - Unemployment duration

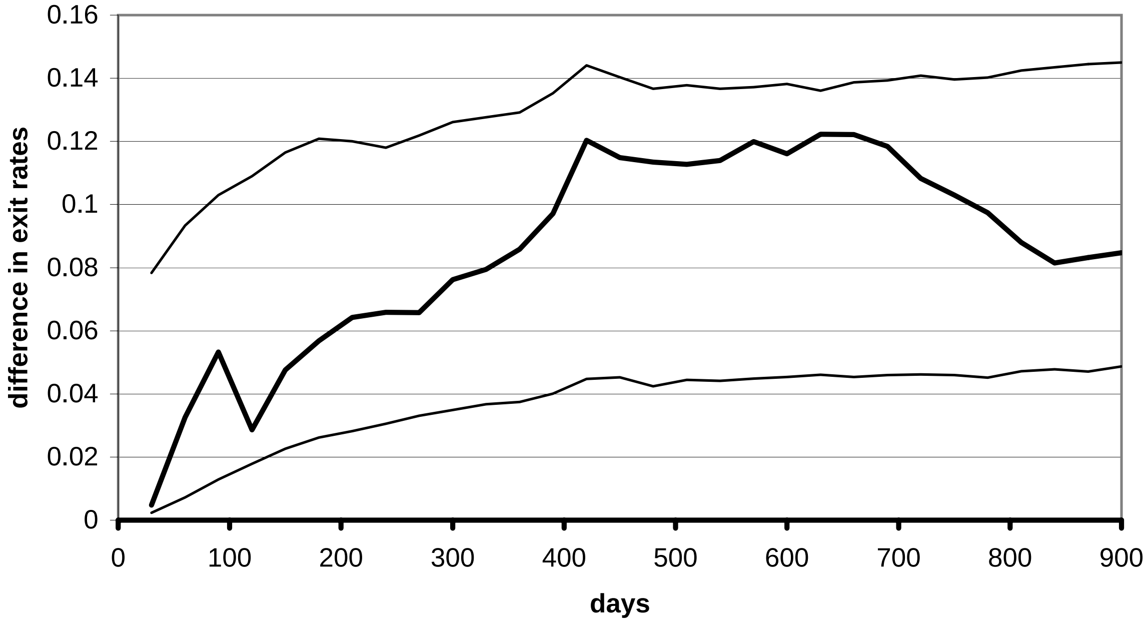
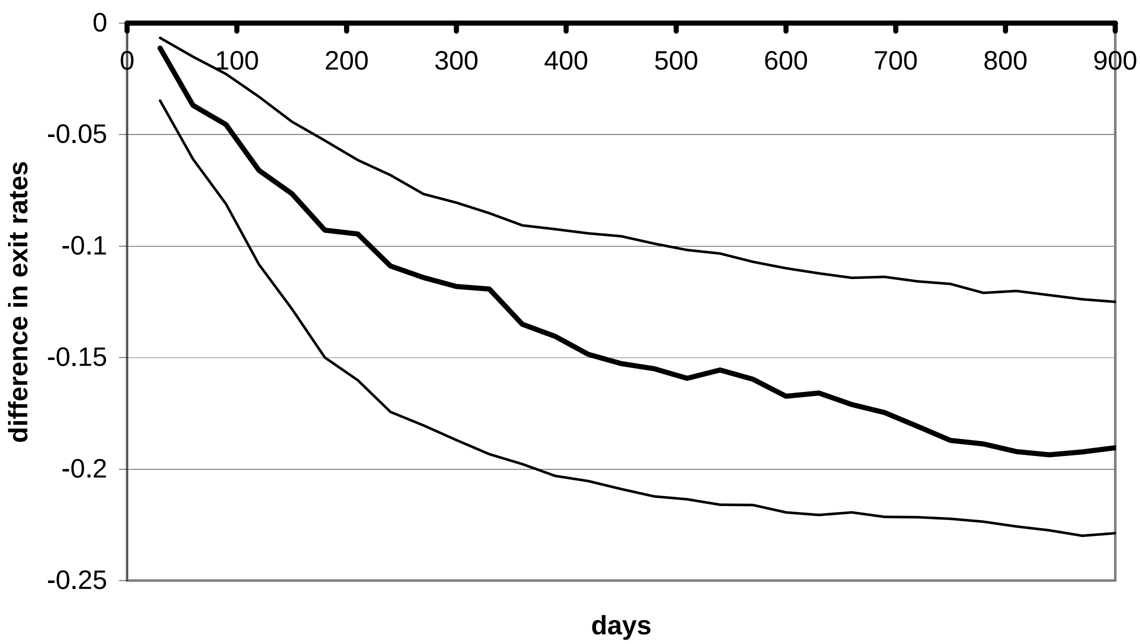


Figure 8b: Effect of job-search support on the treated with conf. int. - Employment duration



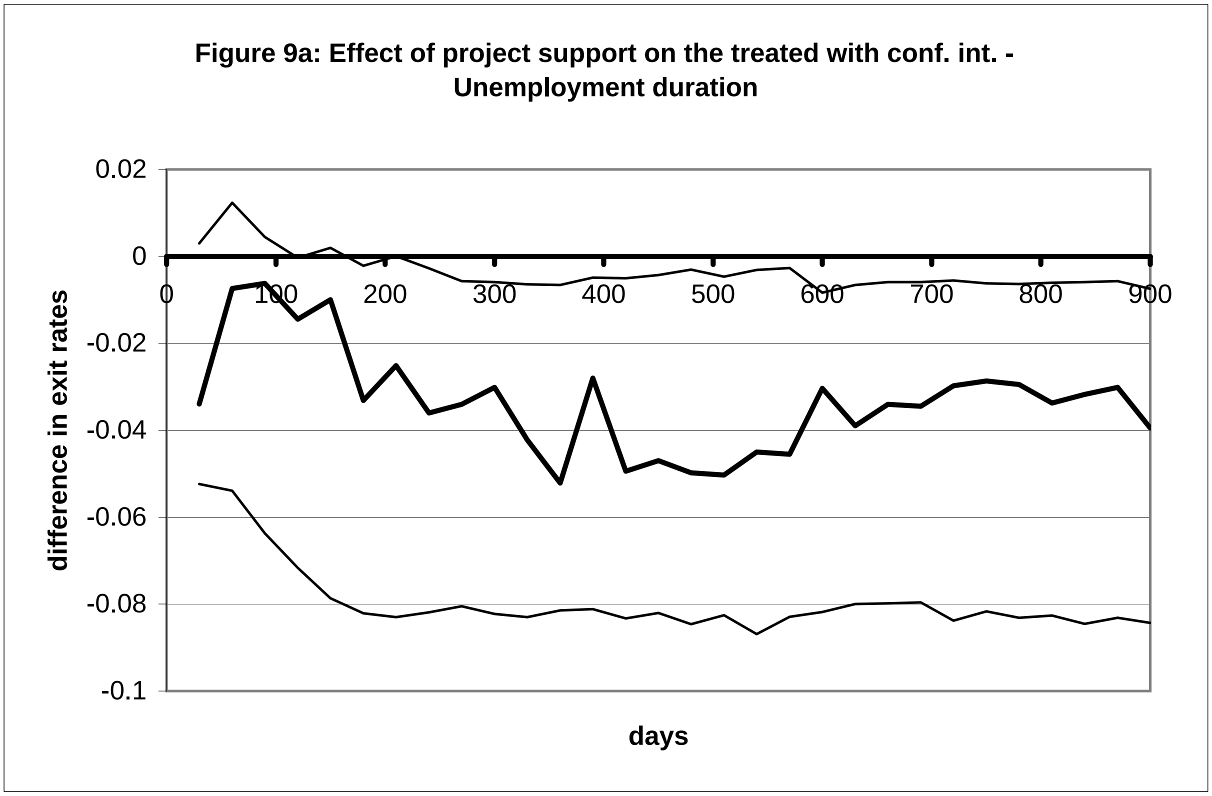


Figure 9a: Effect of project support on the treated with conf. int. -
Unemployment duration
0.02
0
-0.02
-0.04
-0.06
-0.08
-0.1
0
100
200
300
400
500
600
700
800
900
difference in exit rates
days

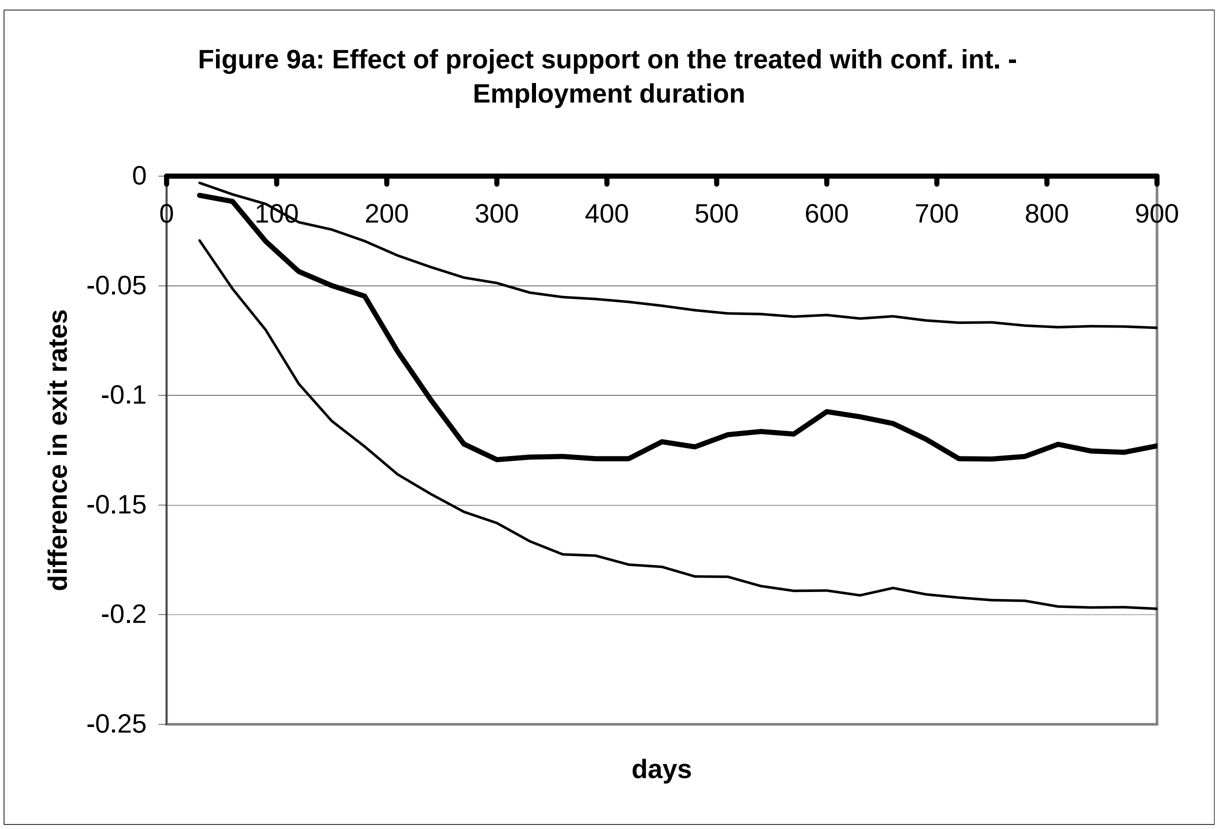


Figure 9a: Effect of project support on the treated with conf. int. -
Employment duration
0
-0.05
-0.1
-0.15
-0.2
-0.25
0
100
200
300
400
500
600
700
800
900
difference in exit rates
days

Appendix

Appendix 1 : Proof of proposition 1

Using equations (1) and (2) we get:

$$S_0(y) = \frac{y - r(V_{u0} + \Pi_v)}{r+q} \tag{30}$$

$$S_1(y) = \frac{y - r(V_{u1} + \Pi_v) + q(V_{u1} - V_{u0})}{r+q} \tag{31}$$

We assume that in the wage bargaining, the worker of type i obtains a share γ of the surplus $S_i(y)$. So the bargaining outcome must satisfy $V_i(y) - V_{ui} = \gamma S_i(y)$ and $\Pi_i(y) - \Pi_v = (1-\gamma) S_i(y)$ for $i = 0, 1$. Workers of type i and employers have an incentive in creating jobs with productivity such that $S_i(y) > 0$. Using equations (30) and (31), and applying the free entry condition $\Pi_v = 0$, jobs are created when productivity exceed reservation productivity y_{ci} in each type of jobs given by:

$$y_{c0} = rV_{u0} \tag{32}$$

$$y_{c1} = rV_{u1} + q(V_{u1} - V_{u0})$$

which implies that $(y_{c1} - y_{c0}) = (r+q)(V_{u1} - V_{u0})$: the value of unemployment for treated is higher if their reservation productivity is higher. Since $V_i(y) - V_{ui} = \gamma S_i(y) = \gamma \frac{y - y_{cI}}{r+q}$, we can express the expected utilities of unemployment under non-participation and participation as:

$$rV_{u0} = b + \lambda_{0,1}(V_{u1} - V_{u0}) + \frac{\gamma \lambda_{0,e}}{r+q} Q_y(y_{c0}) \tag{33}$$

and

$$rV_{u1} = b + \frac{\gamma \lambda_{1,e}}{r+q} Q_y(y_{c1}) \tag{34}$$

reservation productivities are therefore solution of equations

$$\begin{aligned} y_{c0} &= b + \frac{\gamma \lambda_{0,e}}{r+q} Q_y(y_{c0}) + \frac{\lambda_{0,1}}{r+q}(y_{c1} - y_{c0}) & (35) \\ (r + \lambda_{0,1})(y_{c1} - y_{c0}) &= \gamma \lambda_1 Q_y(y_{c1}) - \gamma \lambda_0 Q_y(y_{c0}) & (36) \end{aligned}$$

Since $H(y)$ is a decreasing function and $\lambda_{0,e} < \lambda_{1,e}$, we can show [by contradiction] that $y_{c1} > y_{c0}$ We therefore deduce that $V_{u1} > V_{u0}$

For small treatment, notice that $(r + \lambda_{0,1})(y_{c1} - y_{c0}) = \gamma \lambda_1 Q_y(y_{c1}) - \gamma \lambda_0 Q_y(y_{c0}) = \gamma \lambda_0 Q_y(y_{c1}) - \gamma \lambda_0 Q_y(y_{c0}) + \gamma(\lambda_1 - \lambda_0) Q_y(y_{c0})$ Thus

$$\left(r + \lambda_{0,1} + \gamma \lambda_0 \overline{F}_y(y_0)\right)(y_{c1} - y_{c0}) = \gamma Q_y(y_{c0})(\lambda_1 - \lambda_0)$$

Therefore $(y_{c1} - y_{c0})$ only depend on $(\lambda_1 - \lambda_0)$ at the first order.

Using equations (2) and (30) for workers of type 0 and equations (1) and (31) for workers of type 1, we can derive the wage equations for each worker type:

$$w_0(y) = \gamma y + (1-\gamma) rV_{u0} \tag{37}$$

$$w_1(y) = \gamma y + (1-\gamma)(rV_{u1} + q(V_{u1} - V_{u0})) \tag{38}$$

For a given value y of productivity, the wage depends on whether the worker has been previously treated or not. We have that:

$$w_1(y) > w_0(y) \Longleftrightarrow V_{u1} > V_{u0} \tag{39}$$

Appendix 2 : Proof of proposition 2

This comes from $y_c < y_{c0}$. In an environment without counseling, the reservation productivity is given by:

$$y^* = rV_u \tag{40}$$

where the expected utility of unemployment satisfies:

$$rV_u = b + \frac{\gamma\lambda_{0,e}}{r+q}\int_{y_c}^{\infty}(y-y^*)\,dF_y(y) \tag{41}$$

that is

$$y^* = b + \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y^*) \tag{42}$$

Now the function $y - b - \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y)$ is increasing (because Q_y is decreasing), As $y_{c0} - b - \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y_{c0}) = \frac{\lambda_{0,1}}{r+q}(y_{c1} - y_{c0}) > 0$ and $0 = y^* - b - \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y^*)$ we deduce that $y_c < y_{c0}$

As $y_{c0} = b + \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y_{c0}) + \frac{\lambda_{0,1}}{r+q}(y_{c1} - y_{c0})$ and $y^* = b + \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y^*)$, we have

$$\left[y_{c0} - \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y_{c0})\right] - \left[y^* = b + \frac{\gamma\lambda_{0,e}}{r+q}Q_y(y^*)\right] = \frac{\lambda_{0,1}}{r+q}(y_{c1} - y_{c0})$$

Appendix 3 : Proof of proposition 3

We have the equation

$$(r + \lambda_{0,1})(y_{c1} - y_{c0}) = \gamma\lambda_1 Q_y(y_{c1}) - \gamma\lambda_0 Q_y(y_{c0}) \tag{43}$$

which can be written as

$$y_{c1} - \frac{\gamma\lambda_1}{r+\lambda_{0,1}}Q_y(y_{c1}) = y_{c0} - \frac{\gamma\lambda_0}{r+\lambda_{0,1}}Q_y(y_{c0}) \tag{44}$$

consider $C_0 = y_{c0} - \frac{\gamma\lambda_0}{r+\lambda_{0,1}}Q_y(y_{c0})$. Let $y(\lambda)$ the solution of $y - \frac{\gamma\lambda}{r+\lambda_{0,1}}Q_y(y) = C_0$,.$y_{c1} = y(\lambda_1)$ and $y_{c0} = y(\lambda_0)$. To show that $\lambda_{1,e}\overline{F}_y(y_{c1}) > \lambda_{0,e}\overline{F}_y(y_{c0})$, it is enough to show that $\lambda\overline{F}_y(y(\lambda))$ is an increasing function. We can compute easily that $y'(\lambda) = \frac{\gamma}{r+\lambda_{0,1}}Q_y(y) \Big/ \left(1+\frac{\gamma\lambda}{r+\lambda_{0,1}}\overline{F}_y(y)\right)$

$$\begin{aligned}
\left(\lambda\overline{F}_y(y(\lambda))\right)' &= \overline{F}_y - \lambda f_y(y)\, y'(\lambda) \\
&= \frac{\overline{F}_y\left(1+\frac{\gamma\lambda}{r+\lambda_{0,1}}\overline{F}_y(y)\right) - \frac{\gamma}{r+\lambda_{0,1}}Q_y(y)\,\lambda f_y(y)}{1+\frac{\gamma\lambda}{r+\lambda_{0,1}}\overline{F}_y(y)} \\
&= \frac{\overline{F}_y\frac{r+\lambda_{0,1}}{\gamma\lambda} + \overline{F}_y^2(y) - Q_y(y)\, f_y(y)}{\frac{r+\lambda_{0,1}}{\gamma\lambda} + \overline{F}_y(y)}
\end{aligned}$$

Therefore

$$\left(\lambda\overline{F}_y(y(\lambda))\right)' > 0 \Leftarrow \overline{F}_y^2(y) - Q_y(y)\, f_y(y) > 0$$

notice that we could use $\frac{r+\lambda_{0,1}}{\gamma\lambda} = Q_y(y_{c0})/(y_{c0}-C_0) > Q_y(y_{c0})/(y_{c0})$, if $C_0 > 0$, and obtain a milder condition as shown in Van den Berg van der Klaauw the inequality is equivalent to $d\ln E_y(y\,|y>x)/\,d\ln(x) < 1$ which is true if $yf_y(y)/\overline{F}_y$ is non-decreasing. However it turns out that it not so easy to show that $C_0 > 0$.

Appendix 4: Proof of proposition 4 and 5

Standard computation leads to

$$\begin{aligned}
S(y+\varepsilon) &= \frac{y+\lambda S_\lambda(y)+\varepsilon - rV_{u0}}{r+\lambda} \\
S_0(y) &= \frac{y+\lambda S_\lambda(y)+\varepsilon_u - rV_{u0}}{r+\lambda} \qquad (45)\\
S_1(y) &= \frac{y+\lambda S_\lambda(y)+\varepsilon_u - rV_{u1} - \lambda(V_{u1}-V_{u0})}{(r+\lambda)} \qquad (46)
\end{aligned}$$

where $S_\lambda(y) = \int \max(S(y+\varepsilon), 0)\, dG_\varepsilon(\varepsilon)$. Jobs with productivity y are kept as long as $S(y+\varepsilon) > 0$, i.e. $\varepsilon > \varepsilon_d(y)$, with

$$\begin{aligned}
\varepsilon_d(y) &= (r+\lambda)V_{u0} - \lambda(\Pi_\lambda(y)+V_\lambda(y)) - y \qquad (47)\\
&= rV_{u0} - \lambda S_\lambda(y) - y
\end{aligned}$$

as

$$\begin{aligned}
S_\lambda(y) &= \int \frac{\varepsilon-\varepsilon_d(y)}{r+\lambda} 1(\varepsilon > \varepsilon_d(y))\, dF_\varepsilon(\varepsilon) = \frac{1}{r+\lambda}Q_\varepsilon(\varepsilon_d(y)) \\
&= \frac{1}{r+\lambda}Q_\varepsilon(rV_{u0} - \lambda S_\lambda(y) - y) \qquad (48)
\end{aligned}$$

we have

$$rV_{u0} - y - \lambda S_\lambda(y) + \frac{\lambda}{r+\lambda}Q_\varepsilon(rV_{u0} - \lambda S_\lambda(y) - y) = rV_{u0} - y \qquad (49)$$

From which it follows that

$$\varepsilon_d(y) = G(rV_{u0} - y) \tag{50}$$

where G is defined $x + \frac{\lambda}{r+\lambda} Q_\varepsilon(x) = z \Longleftrightarrow x = G(z)$ is an increasing function

$$G' = \frac{r+\lambda}{r+\lambda-\lambda\overline{F}_\varepsilon(G(z))} > 0$$

It follows therefore the important result for proposition 5 that $\varepsilon_d(y)$ is a decreasing function of y. A job is created from a match between a firm and a non treated unemployed worker if $S_0(y) > 0$, that is $y + \lambda S_\lambda(y) > rV_{u0} - \varepsilon_u$ which can be written as $\varepsilon_d(y) < \varepsilon_u$. As $\varepsilon_d(y)$ is a decreasing function of y, a job is created if $y > y_{c0}$ with

$$\varepsilon_d(y_{c0}) = \varepsilon_u$$

A job is created from a match between a firm and a treated unemployed worker if $S_1(y) > 0$, that is if $y + \lambda S_\lambda(y) > rV_{u1} + \lambda(V_{u1} - V_{u0}) - \varepsilon_u$ which is also $\varepsilon_d(y) < \varepsilon_u - (r+\lambda)(V_{u1} - V_{u0})$. Thus the job is created if $y > y_{c1}$ with

$$\varepsilon_d(y_{c1}) = \varepsilon_u - (r+\lambda)(V_{u1} - V_{u0})$$

which requires that $V_{u1} \geq V_{u0}$The expression of the surplus can be written as

$$\begin{aligned} S_0(y) &= \frac{y + S_\lambda(y) - y_{c0} - S_\lambda(y_0)}{r+\lambda} 1(y > y_{c0}) = \frac{\varepsilon_d(y_{c0}) - \varepsilon_d(y)}{r+\lambda} 1(y > y_{c0}) \\ S_1(y) &= \frac{y + S_\lambda(y) - y_{c1} - S_\lambda(y_1)}{r+\lambda} 1(y > y_{c1}) = \frac{\varepsilon_d(y_{c1}) - \varepsilon_d(y)}{r+\lambda} 1(y > y_{c1}) \end{aligned}$$

from which and $V_1(y) - V_{u1} = \gamma S_1(y)$, $V_0(y) - V_{u0} = \gamma S_0(y)$, we deduce that

$$\begin{aligned} rV_{u0} &= b + \lambda_{0,1}(V_{u1} - V_{u0}) + \frac{\lambda_{0,e}\gamma}{r+\lambda} \int_{y>y_{c0}} (\varepsilon_d(y_{c0}) - \varepsilon_d(y)) \, dF_y(y) \\ rV_{u1} &= b + \frac{\lambda_{1,e}\gamma}{r+\lambda} \int_{y>y_{c1}} (\varepsilon_d(y_{c1}) - \varepsilon_d(y)) \, dF_y(y) \end{aligned}$$

Assume that $y_{c1} \leq y_{c0}$. This is equivalent to $\varepsilon_d(y_{c1}) \geq \varepsilon_d(y_{c0})$.
Therefore $\int_{y>y_{c1}} (\varepsilon_d(y_{c1}) - \varepsilon_d(y)) \, dF_y(y) \geq \int_{y>y_{c0}} (\varepsilon_d(y_{c0}) - \varepsilon_d(y)) \, dF_y(y)$ and thus $\lambda_{1,e} \int_{y>y_{c1}} (\varepsilon_d(y_{c1}) - \varepsilon_d(y)) \, dF_y(y) \geq \lambda_{0,e} \int_{y>y_{c0}} (\varepsilon_d(y_{c0}) - \varepsilon_d(y)) \, dF_y(y)$ which implies that $rV_{u1} \geq rV_{u0} - \lambda_{0,1}(V_{u1} - V_{u0})$, that is $V_{u1} \geq V_{u0}$. This leads to a contradiction given the expression of $\varepsilon_d(y_{c1}) \geq \varepsilon_d(y_{c0})$
given $\varepsilon_d(y_{c1}) = \varepsilon_u - (r+\lambda)(V_{u1} - V_{u0})$.

The duration of the first job after exit from unemployment is higher for treated unemployed workers than for untreated unemployed workers:

$$q(y_{c1}) = \lambda P(\varepsilon < \varepsilon_d(y_{c1})) < q(y_{c0}) = \lambda P(\varepsilon < \varepsilon_d(y_{c0})) \tag{51}$$

Since $y_{c1} > y_{c0}$ by result 1 (a result that carries over in this setting), the proof consists in showing that $\varepsilon_d(y)$ is a decreasing function of y.

The extension of proposition 2 to the setting of endogenous job destruction follows from the fact that in an environment without treatment the reservation productivity is given by $G\left(rV_u^* - y^*\right) = \varepsilon_u$

$$rV_u^* = b + \frac{\lambda_{0,e}\gamma}{r+\lambda} \int_{y>y^*} \left(\varepsilon_u - \varepsilon_d\left(y\right)\right) dF_y\left(y\right) v$$

with $\varepsilon_d\left(y\right) = G\left(rV_u^* - y\right)$.

If we consider the function $\vartheta\left(V_u^*\right) = rV_u^* - \frac{\lambda_{0,e}\gamma}{r+\lambda} \int_{y>y^*} \left(\varepsilon_u - \varepsilon_d\left(y\right)\right) dF_y\left(y\right)$, V_u^* is defined by $\vartheta\left(V_u^*\right) = b$, and V_{u0} is defined by $\vartheta\left(V_{u0}\right) = b + \lambda_{0,1}\left(V_{u1} - V_{u0}\right)$, ϑ is an increasing function and therefore $V_u^* < V_{u0}$, which leads to the conclusion. Notice that here also $\vartheta\left(V_u^*\right) - \vartheta\left(V_{u0}\right) = -\lambda_{0,1}\left(V_{u1} - V_{u0}\right)$. Therefore the difference is of second order.

Appendix 5: Proof of proposition 6

We want to show that

$$\lambda_{1,e}\overline{F}_y\left(y_{c1}\right) > \lambda_{0,e}\overline{F}_y\left(y_{c0}\right)$$

given

$$\begin{aligned} & \varepsilon_d\left(y_{c1}\right) + \frac{\lambda_{1,e}\gamma}{r+\lambda_{0,1}} \int_{y>y_{c1}} \left(\varepsilon_d\left(y_{c1}\right) - \varepsilon_d\left(y\right)\right) dF_y\left(y\right) \\ = \; & \varepsilon_d\left(y_{c0}\right) + \frac{\lambda_{0,e}\gamma}{r+\lambda_{0,1}} \int_{y>y_{c0}} \left(\varepsilon_d\left(y_{c0}\right) - \varepsilon_d\left(y\right)\right) dF_y\left(y\right) \end{aligned}$$

introducing $\varepsilon_{dj} = \varepsilon_d\left(y_{cj}\right)$, changing $z = \varepsilon_d\left(y\right)$, denoting $\Phi\left(z\right)$ the cdf of $z : \Phi\left(z\right) = \overline{F}_y \circ \varepsilon_d^{-1}\left(z\right)$, and ϕ its density, the previous equation writes

$$\varepsilon_{d_0} + \frac{\lambda_{0,e}\gamma}{r+\lambda_{0,1}} \int_{z<\varepsilon_{d0}} \left(\varepsilon_{d0} - z\right) d\Phi\left(z\right) = \varepsilon_{d_2} + \frac{\lambda_{1,e}\gamma}{r+\lambda_{0,1}} \int_{z<\varepsilon_{d1}} \left(\varepsilon_{d1} - z\right) d\Phi\left(z\right)$$

and the proof is as in the preceding case.

Appendix 6: Identification conjecture

Consider a model with three durations: unemployment with no treatment (t_0), unemployment with a treatment (t_1) and a subsequent employment duration (t_E). In the mixed proportional hazard model, all marginal distributions are identified by duration data, provided a set of technical assumptions and normalizations are assumed. Also, the observed correlation between t_0 and t_1, conditional on observed covariates, identifies the joint distribution of their unobserved components, v_0 and v_1. Therefore, the probability that the individual that enters employment was treated or not, is known.

Set $P = 1$ if the individual was treated before entering employment. Dropping the observed covariates to simplify notations, we write the hazard rate from employment to unemployment:

$$h(t_E) = \theta(t_E)\gamma^P v_E$$

We observe the distribution of durations t_E that followed unemployment with no treatment for a set of durations t_0: $f(t_E|t_0)$. This identifies $f(v_E|v_0)$ because:

$$f(t_E|t_0) = \int_{v_E} \theta(t_E) v_E \left[\exp(-\int_0^{t_E} \theta(s)ds)\right]^{v_E} f(v_E|v_0) dv_E$$

and all parameters, except that of the conditional distribution $f(v_E|v_0)$ are already identified.

Accordingly, we observe the distribution of durations t_E that followed unemployment with a treatment for a set of durations t_1: $f(t_E|t_1)$. We have:

$$f(t_E|t_1) = \int_{v_E} \theta(t_E)\gamma v_E \left[\exp(-\int_0^{t_E} \theta(s)ds)\right]^{\gamma v_E} f(v_E|v_1)dv_E$$

Again, all parameters, except that of the conditional distribution $f(v_E|v_1)$ are already identified. Still, this equation alone identifies this conditional distribution only up to a nomalization $(1/\gamma)$. As such, it does not identify separately the selection and the causal effect. However, the necessary normalization $E(v_E) = 1$ that applies to the entire model already normalizes $f(v_E|v_1)$. Indeed:

$$E(v_E) = \int_{v_0} E(v_E|v_0)f(v_0)dv_0 \times \Pr(P=0) + \int_{v_1} E(v_E|v_1)f(v_1)dv_1 \times \Pr(P=1)$$

Every term, except $E(v_E|v_1)$, is already identified, without the information on $f(t_E|t_1)$. Therefore, this equation normalizes $f(v_E|v_1)$ and the causal parameter γ can be recovered from the empirical distribution of $f(t_E|t_1)$.

Appendix 7: Endogeneous sampling

Consider two strata : $Strata_2 = \{i|\, T_i \notin \{S_1, S_2, A_1, A_2\}\ \&\ Exit_i = 0\}$ and $Strata_1 = \complement Strata_2$. The sample rates in each strata are denoted π_s, we have $\pi_1 = 1$,and π_2 determined by $\pi_1 f_1 + \pi_2 f_2 = \Pi_S = 10\%$. where f_i is the frequency of strata i in the population and Π_S is the average sampling rate.

The joint likelihood of the dependent and explanatory variables is

$$g(y,z;\beta) = (\pi_1 R_1(y) + \pi_2 R_2(y))\, f(y,z;\beta) = (\pi_1 R_1(y) + \pi_2 R_2(y))\, f(y\,|z\,;\beta)\, f(z) \tag{52}$$

where $R_s(y)$ are the two functions taking values 1 when the observation y belongs to strata s and 0 if not. The main problem with endogeneous sampling comes from the unknown density of exogenous variables. In the endogenous sample this depends on the parameter of interest and cannot therefore be factored out as in a random sample.

$$\begin{aligned} g(z;\beta) &= f(z)\int \sum_{s=1}^{2} \pi_s R_s(y)\, f(y\,|z\,;\beta)\, dy = f(z)\sum_{s=1}^{2}\pi_s \int R_s(y)\, f(y\,|z\,;\beta)\, dy \\ &= f(z)\sum_{s=1}^{2}\pi_s f_s(\beta) \end{aligned} \tag{53}$$

Following Manski Lerman (1977), we obtain a consistent estimator by maximizing the weighted likelihood :

$$\sum_i \sum_{s=1}^{2} w_s R_s(y_i)\, Log\,(f(y_i\,|z_i\,)) \tag{54}$$

where w_s is the weight chosen for the of observations in strata s. The limit value of the objective function is

$$\sum_{s=1}^{2} w_s \int_{y \in s} g\left(y, z; \beta\right) Log\left(f\left(y \left| z\right.; \beta\right)\right) = \sum_{s=1}^{2} w_s \pi_s \int_{y \in s} f\left(y \left| z\right.; \beta_0\right) f\left(z\right) Log\left(f\left(y \left| z\right.; \beta\right)\right) \tag{55}$$

A consistent estimator is clearly obtained for $w_s = 1 \left/ \pi_s\right.$. The estimator is consistent and asymptotically normal, but as the objective is no longer a likelihood, the variance has not the standard expression for maximum likelihood estimators of the expectation of the cross product of the derivative and is given by the usual formula $J^{-1} I J^{-1}$, where $J = E\left[-\sum\limits_{s=1}^{2} w_s 1_{s_i = s} \nabla_{\beta\beta'} Log\left(f\left(y_i \left| z_i\right.\right)\right)\right]$ and $I = V\left(\sum\limits_{s=1}^{2} w_s 1_{s_i = s} \nabla_{\beta} Log\left(f\left(y_i \left| z_i\right.\right)\right)\right)$.

Another approach could have been to perform Conditional Maximum Likelihood, based on

$$\frac{g\left(y, z; \beta\right)}{g\left(z; \beta\right)} = \frac{\sum\limits_{s=1}^{2} \pi_s R_s\left(y\right) f\left(y \left| z\right.; \beta\right) f\left(z\right)}{f\left(z\right) \sum\limits_{s=1}^{2} \pi_s f_s\left(z, \beta\right)} = \frac{\sum\limits_{s=1}^{2} \pi_s R_s\left(y\right) f\left(y \left| z\right.; \beta\right)}{\sum\limits_{s=1}^{2} \pi_s f_s\left(z, \beta\right)} \tag{56}$$

where $f_s\left(z, \beta\right) = P\left(s \left| z\right.; \beta\right)$ which is not necessarily more efficient than the Manski Lerman estimator and far more complicated to implement as this requires the computation of the probabilities $f_s\left(\beta\right)$, and their introduction within which would increase the non linearity of the objective function.

Full Information Maximum Likelihood would have led to the most efficient estimator. FIML is a semi parametric estimation based on the joint density of the explanatory and dependent variable, in which the density of the explanatory variables is treated as a nuisance parameter. The likelihood is concentrated in the corresponding nuisance parameters. Although this procedure is more efficient, we did not implement it as it would have complicated too much an already complicated objective function which maximisation is not straightforward, involving many local maxima.