Using Matching Estimators to Evaluate Alternative Youth Employment Programs: Evidence from France, 1986-1988.*

Thomas Brodaty† Bruno Crépon‡ Denis Fougère§

1. Introduction

In this paper we apply the statistical framework developed by Imbens (1999) and Lechner (1999) to identify and to estimate the causal effects of multiple treatments under the conditional independence assumption. The application concerns the youth employment programs which were set up in France during the eighties to improve the labor market prospects of the most disadvantaged and unskilled young workers. The empirical analysis makes use of non-experimental longitudinal micro data collected by INSEE (Institut National de la Statistique et des Etudes Economiques, Paris) from 1986 to 1988. These data are based on administrative records supplemented by a series of four interviews over one and a half years; they provide information on the dates of entry into training programs and on durations of subsequent spells of employment and unemployment. These data were previously used by Bonnal, Fougère and Sérandon (1997) to estimate the impact of youth employment schemes on subsequent unemployment and employment du-

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†Eurequa, Université Paris-I.

‡INSEE-CREST, Paris

§CNRS ans CREST-INSEE, Paris.

rations of recipients using a reduced-form multi-state multi-spell transition model that includes participation in these programs as an additional state.

In this paper, we propose to re-examine the impact of these programs on the subsequent employment status by implementing matching estimators, which were recently studied by Heckman, Ichimura, Smith and Todd (1998) and Heckman, Ichimura and Todd (1998). Such estimators are derived from a causal model and their identification do not rely on the assumption of constant treatment effects and on distributional assumptions.

Let us recall briefly the statistical framework which is presented more extensively in Imbens (1999) and Lechner (1999). Evaluation methods usually try to compare two potential outcomes which are associated with two regimes, generally called treatment and non treatment. Identification assumptions as well as estimation methods have been extensively studied in this context. The conditional independence assumption, which states that the assignment to treatment T and the response variable Y are conditionally independent given observable covariates X, has received a lot of attention. It leads to various estimation methods in which the propensity score of being treated plays a key role. However, treatments are usually not homogenous in practice, at least in the field of the evaluation of active labor market policies. The treatment status is the aggregation of various treatments whose efficiency may strongly differ. So it is of interest to adapt the previous methods to the case where mutually exclusive treatments are possible, and to examine how their relative efficiency can be estimated. We introduce K treatments. The assignment to one specific treatment k is defined by $T(k) = 1$, and the potential output associated with treatment k is denoted $Y(k)$. Our parameters of interest are $E(Y(l) - Y(m) \mid T(l) = 1)$. For identifying the relative effect of treatment l with respect to treatment m, we assume that $Y(m) \perp T(l) \mid x$. Then we apply matching methods developped by Heckman et al. (1998) to the individuals who receive treatments l or k. Thus our evaluation of treatment l against treatment k is not the same as our evaluation of treatment k against treatment l.

The literature on estimation by matching has often emphasized the importance of the propensity score specification. Due to the fact that our sample is extracted from the stock of unemployed people at a given date (August 1986), a natural specification of the treatment probabilities may be derived from a competing-risks duration model. Our results highlight the variability of program effects, both between programs and among recipients of the same program. We also show that, when one program performs on average better than another one, its relative efficiency tends to increase with the ratio of the propensity scores.

In the next Section, we recall the general framework for the evaluation problems with multiple treatments and we show that, under the conditional independence assumption, matching with respect to the ratio of the scores $P(T_i = l \mid X_i)$ and $P(T_i = k \mid X_i)$ allows to estimate nonparametrically the average conditional treatment effect $E(Y_{l,i} - Y_{m,i} \mid T_i = l)$ for a pair of treatments l and m. Section 3 gives a description of youth employment programs in France and Section 4 presents the data we use. In Section 5, we introduce the specification of our propensity scores, which are derived from a competing-risks duration model, and we discuss their estimates. In Section 6, we report and comment the results obtained for different response variables through kernel matching estimation. Section 7 concludes.

2. The Evaluation Problem with Multiple Treatments.

The general framework that we use is the one developed by Imbens (1999) and Lechner (1999) for the evaluation of programs involving multiple exclusive treatments. This framework generalizes the modelling that Rubin (1974,1977) introduced for the case of a unique treatment. Let us recall briefly the formalism introduced by Imbens (1999) and Lechner (1999). We assume that there are $K+1$ exclusive treatments, denoted $0, 1, \ldots, K$, the value 0 corresponding to the absence of treatment. For the individual i, the assignment to a given treatment is indicated by the variable T_i taking values in $\{0, 1, \ldots, K\}$. $K+1$ potential outputs, which are denoted $Y_{0,i}, Y_{1,i}, \cdots, Y_{K,i}$, are associated with the $K+1$ possible treatments.

The identifying assumption studied in these papers is the conditional independence of the treatment indicator and the potential outputs given the values of the observable covariates. This assumption means that there exists a set of observables X_i such that $(Y_{0,i}, Y_{1,i}, \cdots, Y_{K,i}) \perp T_i \mid X_i$. As a generalization of Rubin's results, various parameters of the distribution of treatment effects may be identified for any pair of treatments $\{l, m\}$; for instance, we may then identify the average unconditional effect of treatment l with respect to treatment m, equal to $E(Y_{l,i} - Y_{m,i})$, or the average conditional effect given that individual i is assigned to treatment l, denoted $E(Y_{l,i} - Y_{m,i} \mid T_i = l)$. Lechner (1999) also considers the conditional expectation $E(Y_{l,i} - Y_{m,i} \mid T_i \in \{l, m\})$, which is specific to this framework.

The estimation methods of these parameters can be based either on matching methods, initially proposed by Rubin (1977) and then extended by Rosenbaum and Rubin (1983), or on the weighting techniques proposed by Dehedjia and Whabba (1995) for the case of two treatments. Recently matching estimators applied to the case of a unique treatment have received a lot of attention. This increased interest is due to the particularly appealing result obtained by Rosenbaum and Rubin (1983) who have shown that matching on the propensity score of being treated (given the values of the observed covariates) achieves to remove the selectivity bias. Recently this procedure was extensively studied by Heckman and his coauthors in a series of papers where the matching principle is extended through kernel or nearest neighbour techniques to provide a non parametric estimate of the treatment effect given the value of the propensity score (see, for instance, Heckman, Ichimura and Todd, 1998, Heckman, Ichimura, Smith and Todd, 1998, and Heckman and Smith, 1999).

In this paper, we mainly focus on average conditional treatment effects given assignment to treatment l, namely $E\left(Y_{l,i} - Y_{m,i} \mid T_i = l\right)$. Results available up to now require to match observations simultaneously on the two scores $P\left(T_i = l \mid X_i\right)$ and $P\left(T_i = m \mid X_i\right)$. The following proposition shows that matching with respect to the ratio of these scores is sufficient to remove the selectivity bias. In this context, it is therefore possible to use directly the kernel matching techniques developed by Heckman, Ichimura and Todd (1998) and Heckman, Ichimura, Smith and Todd (1998) to estimate our parameters of interest.

Proposition 1. *If the conditional independence assumption*

$$\left(Y_{0,i}, Y_{1,i}, \cdots, Y_{K,i}\right) \perp T_i \mid X_i$$

holds, then

$$\left(Y_{l,i}, Y_{m,i}\right) \perp T_i \mid \Pi^{l \backslash m}\left(X_i\right), T_i \in \{l, m\}$$

where $\Pi^{l \backslash m}\left(X_i\right) = \dfrac{\Pi^l\left(X_i\right)}{\Pi^l\left(X_i\right) + \Pi^m\left(X_i\right)}$, *and* $\Pi^l\left(X_i\right) = P\left(T_i = l \mid X_i\right)$.

Proof. See Appendix.

Two estimation methods may be derived from this property. The first method is the comparison of weighted means of outputs, and the second one is a matching procedure.

Proposition 2. **Estimation through weighting.**

Under the conditional independence assumption, the average conditional treatment effect $E(Y_{l,i} - Y_{m,i} \mid T_i = l)$ *given assignment to treatment* l *may be estimated as*

$$E(Y_{l,i} \mid T_i = l) - E(Y_{m,i} \mid T_i = l) = E(Y \mid T_i = l) - E\left(Y \frac{\Pi^l(X_i)}{\Pi^m(X_i)} \frac{P^m}{P^l} \mid T_i = m\right)$$

where $P^l = P(T_i = l)$ *and* $P^m = P(T_i = m)$.

Proof. See Appendix.

Proposition 3. Estimation through matching.

To estimate the average conditional treatment effect $E(Y_{l,i} - Y_{m,i} \mid T_i = l)$ *given assignment to treatment* l*, it is possible to match individuals receiving treatment* l *with individuals receiving treatment* m *on the basis of the ratio* $\Pi^{l\backslash m}(X_i)$ *of the scores.*

Proof. See Appendix.

3. Youth Employment Programs in France

Over the last twenty years, youth unemployment is the most striking feature of the French labor market. For workers between 15 and 24 years old, the unemployment rate increased from 13% in 1979 to 26.6% in 1999, after reaching a maximum, 29%, in 1987. This explains why active labor market policies were increasingly introduced in France since the mid-seventies, when unemployment started its increase (see DARES, 1996, for a historical description). These policies were targeted to the unemployed as well as to workers with the highest unemployment risks, among which young adults or older workers. These policies are similar to those implemented in other European countries (Scarpetta, 1993), France being a median user. Direct employment subsidies and incentives for human capital investments are the two main instruments of these policies. Almost any mixture of these two components can be found within French employment policies. For instance, public employment schemes such as community jobs (Travaux d'Utilité Collective, TUC) or the more recent program called "Contrats Emploi Solidarité" (CES) have almost no component of training or learning by doing. At the other extreme, apprentice contracts have a very intensive training content.

Approximately fifty measures were implemented since 1974, even though only ten programs are still in use. These programs may be classified according to the characteristics of eligible participants, the level of implementation (local or national), the employment sector (public or private), or the legal status (training course or labor contract). Each year, 800,000 individuals between 15 and 25 years old are financially assisted through public programs which give them a training course or a subsidized job.[1]

Behind this profusion of measures, two main types of public interventions can be distinguished:

1. job creation in the public sector, thanks to massive wage subsidies, directed to low-skilled unemployed young adults,

2. promotion of training programs in the private sector, these programs include classroom education and on-the-job training in order to increase labor market experience and human capital.

There are just a few empirical studies using French data that adopt the spirit of the literature on program evaluations (Heckman and Smith, 1995). Almost all of them use observational data, as opposed to experimental data. In addition, just a few among the few control for selection bias and unobserved heterogeneity (Bonnal, Fougère and Sérandon, 1997, Magnac, 1997). Their main results can be summarized as follows. Training programs directed at unemployed young persons have no effect on post-training wages or employment probabilities unless they have a large training content. On the other hand, payroll tax subsidies have significant effects on employment probabilities of low-wage workers, but their largest effects concern workers between 25 and 30 (see, Fougère, Kramarz and Magnac, 1999).

Let us now recall the main features of youth training programs which were in effect in France during the late 1980's. Most of these programs were introduced before, but the numbers of participants increased greatly after the 1986 Emergency Plan for Youth Employment ("Plan d'Urgence pour l'Emploi des Jeunes"). This Plan introduced strong incentives for private firms offering training places and facilitated the development of programs with alternating spells of work and training ("formations en alternance", for which we propose the term "workplace training programs"). For instance, the lower age limit for entry into such programs has been lowered from 18 to 16 years old, while the upper age limit for entry into the apprenticeship system has been raised from 20 to 25 years old.

[1] Of course, the number of recipients is lower, because the same young person may benefit from several programs in the same year. Let us recall that the number of recipients was highest in the mid-eighties: in 1987, almost one million young people benefited from the public programs.

To simplify, we can distinguish between two types of programs: the "workplace" training programs provided by private firms (including apprenticeship, qualification and adaptation contracts, and "courses for preparation to the working life"), and the "workfare" programs provided by the State and the public sector (including "community jobs" and "courses for the 16-to-25 years old"). For this second type of programs, the amount of vocational and specific training is generally lower. The apprenticeship contract is a training scheme which offers participants part-time work in the firm, complemented by part-time education in a public training center. Every participant prepares himself/herself for a national diploma; to obtain this diploma, a test has to be taken after completion of the contract. The applicant has to be between 15 and 25 years of age, the applicant must find a firm which is authorized to hire apprentices, and he/she has to be registered in a training center for apprentices ("Centre de Formation pour Apprentis"). The apprenticeship contract, signed both by the employer and the employee, is registered by a local office of the Ministry of Employment and Social Policy. The usual length of an apprenticeship contract is two years, but it can vary between one and three years. The training is partly general, but it also comprises occupation-specific components. The apprentice is a wage-earner, and his/her wage is calculated as a fraction of the minimum wage level (called SMIC in France), according to the apprentice's age and seniority in the contract (between 17 and 75% of the minimum wage level). At the end of the apprenticeship contract, the employee may be hired by the firm either under a fixed-term labor contract (CDD), or under a long-term labor contract (CDI).

The "Contrat de Qualification" is very similar to the apprenticeship contract. It is a fixed-term contract with length that may vary from 6 to 24 months. Every participant prepares himself/herself for a diploma as in apprenticeship contracts. This program is addressed to unskilled or long-term unemployed young adults. At least one-fourth of the contract period must be devoted to training. This training takes place during working hours and is approved by collective agreements. The participant is paid by the employer; the wage is equal to a fixed fraction of the monthly legal minimum wage, and this fraction varies according to the age of the participant and the seniority in the contract. The "Contrat d'Adaptation" may be either a fixed-term labor contract with length that may vary from 6 to 12 months or a long-term labor contract. It is aimed to provide some specific training (adapted to the job). This program is addressed to skilled young people who have difficulties to find a job. Potential employers are all firms in craft, trade and industrial sectors. If the "adaptation contract" is a fixed-term labor contract, at least 200 hours must be devoted to training. If it is signed as a long-term labor contract, the amount of training depends both on the job and on the skill level of the applicant. The wage is paid by the firm; it is at least equal to the legal minimum wage. Firms signing “adaptation contracts” are exempted from paying the employer training tax but have to pay Social Security contributions. “Courses for Preparation to the Working Life” (CPWL, “Stages d’Initiation à la Vie Professionnelle”) are non-renewable fixed-term labor contracts in the private sector, which are aimed to offer some general training to young people with no work experience or who are unemployed for more than one year. The training is provided either by the firm or by a government training center. Trainees receive a lump-sum from the State and a complementary allowance from the firm. Firms offering such courses are exempted to pay Social Security contributions.

The program called ”Travaux d’Utilité Collective” (TUC, or community jobs) was set up in 1984 and suppressed in 1990. Since that date, it has been replaced by the program called ”Contrats Emploi-Solidarité” which has essentially the same characteristics. In these programs, hiring of low-educated jobless young adults and long-term unemployed in community service jobs is heavily subsidized; the objective being not only to give a job but also to increase employability. Employers are public institutions, local administrations and non-profit associations. The “community job” contract is a part-time (20 hours a week) fixed-term (from 3 to 12 months) employment contract. From 1987, contract length has be extended to 24 months for people with poor employment prospects. The hourly wage is the legal hourly minimum wage. It is entirely paid by the State. The employer is exempt from Social Security contributions but not from Unemployment Insurance contributions. ”Courses for 16 to 25 years old” (”Stages pour les 16-25 ans”) were training courses offered by State training centers. Their length varied from 6 to 9 months and the time devoted to training was between 550 and 700 hours. These courses were aimed to facilitate social and professional integration of young people leaving the educational system without any diploma or qualification. Trainees received a lump-sum from the State.

4. The Data

The data for our study are provided by the “Suivi des Chômeurs” survey collected by INSEE (Paris). The sample has been drawn randomly in August 1986 from the files of the public employment service (“Agence Nationale Pour l’Emploi” or ANPE[2]). About 8000 unemployed people were sampled but only 7450 could be reached at the first interview. Individuals were interviewed four times, in November 1986, May 1987, November 1987, and finally May 1988. At the first inquiry, respondents were asked to give information on their labor market status between August and November 1986, and in particular on the time already spent in the unemployment spell sampled in August 1986 and on their status before entry into that spell. The data record retrospectively month after month, between November 1986 and May 1988, the events corresponding to individual transitions in the labor market. For that study, we consider only young men who were less than 27 years old in August 1986 and for whom it is possible to observe an accurate and relevant date of registration in the ANPE files. The subsample includes 3160 individuals. For each individual whose unemployment spell is not right censored, we observe either a transition to a regular job with a long-term duration labor contract (LTC) or with a fixed-term labor contract (FTC), either a transition to the out-of-labor-force (OLF) state, or a transition to one among the following employment programs:

- a workplace training program (an apprenticeship contract, a qualification contract, or an adaptation contract),
- a course for preparation to the working life,
- a community job,
- or a training course "for 16 to 25 years old" (this category is also called "other programs" hereafter).

Among the 3160 individuals in our subsample, we observe:

- 655 initial unemployed spells which are right-censored at the end of the observation period (may 1988),[3]
- 726 transitions from the initial unemployment spell to an LTC job,

[2] These files include all unemployed people registered at the ANPE who were looking either for a full-time or part-time permanent job, or a full-time or part-time temporary job in August 1986. These requirements do not correspond to the definition of unemployment given by the International Labour Office.

[3] The subset of right-censored observations includes the individuals who exited from the panel because of attrition in November 1986, May 1987, or November 1987.

- 703 transitions from the initial unemployment spell to an FTC job,
- 298 transitions from the initial unemployment spell to the OLF state,
- 244 transitions from the initial unemployment spell to a community job,
- 52 transitions from the initial unemployment spell to a workplace training program,
- 194 transitions from the initial unemployment spell to a course for preparation to the working life,
- 284 transitions from the initial unemployment spell to a training course "for 16 to 25 years old".

The treatments we are interested in are these four types of employment programs. A job with a fixed-term labor contract (FTC) is considered as an additional treatment. This allows us to compare each of the four programs with a reference treatment which is not strictly speaking the no-treatment case. This comparison makes sense because these programs and FTC jobs both offer temporary employment to participants. Then the question is to know if, in comparison with FTC jobs, programs facilitate or postpone the access to stable jobs (with long-term labor contracts).

5. Estimation of the Propensity Scores

In all evaluation studies using the propensity score methodology, specifying and estimating the conditional probabilities of receiving the different possible treatments (or transiting to the different programs) is the first and fundamental step. Nonparametric or semiparametric estimation of this conditional model (which may be specified for example as a multiple qualitative response model) is certainly the best strategy. But, as we will see below, stock sampling bias is present in our data, and, at our knowledge, correcting for such a bias is not possible without imposing some additional restrictions on the functional form of the transition probabilities. The potential effect of the unemployment duration on the process of assignment to treatments has naturally led us to derive the conditional probabilities of transiting from unemployment to the various treatments from a competing risks duration model.

5.1. The Duration Model

Figure 1 illustrates the bias due to the fact that the sample has been extracted from the stock of unemployed people in August 1986. For example, on the first graph, we represent the Kaplan-Meier estimate of the overall hazard function of the duration spent in the sampled unemployment spell, which is obtained without any correction of the stock sampling bias, versus the conditional maximum likelihood estimate of a piece wise constant hazard function taking into account some correction of the bias. This correction consists in weighting each observation by the inverse of the probability to be still unemployed at the sample date (august 1986), which is equal to the survivor function of the unemployment duration calculated as the difference between the sampling date and the date of entrance into the sampled unemployment spell. The other graphs represent the same estimates for each specific hazard function associated with a given transition. These graphs show that the unemployment durations sampled from the stock underestimate seriously the hazard function and thus overestimate the average unemployment duration.

To estimate the propensity scores associated with the different programs and employment states, we make use of a competing-risk duration model whose estimation takes into account the stock sampling bias correction. More precisely, we assume that the rate of a transition from unemployment to a given state k $(k = 1, ...7)$ has the following Weibull proportional hazard form

$$h_k(u \mid \beta_k, \alpha_k, X_k) = \alpha_k \times t^{\alpha_k - 1} \times \exp[\beta_k^{'} X_k],\ \alpha_k > 0,$$

where u represents the duration of the unemployment spell. The survivor function for a duration equal to t being

$$S(t \mid \alpha_1, ..., \alpha_7, \beta_1, ..., \beta_7, X_1, ...X_7) = \exp[-\sum\nolimits_{l=1}^{7} t^{\alpha_l} \exp(\beta_l^{'} X_l)].$$

The propensity score, which is equal to the probability that the unemployment spell ends with a transition to a state k $(k = 1, ...7)$ has the form

$$\begin{aligned} \Pr(K &= k \mid \alpha_1, ..., \alpha_7, \beta_1, ..., \beta_7, X_1, ...X_7) \\ &= \int_0^{\infty} \alpha_k t^{\alpha_k - 1} \exp[\beta_k^{'} X_k] \exp[-\sum\nolimits_{l=1}^{7} t^{\alpha_l} \exp(\beta_l^{'} X_l)]\, dt \end{aligned}$$

5.2. Results

5.2.1. The competing-risks duration model

Table 2 shows the parameter estimates of this competing-risks duration model, taking into account our correction of the stock sampling bias. Let us remark that the estimated baseline intensities of transition from unemployment to the program called "Courses for Preparation to the Working Life" (CPWL hereafter) or to the category called "other programs" are constant through the unemployment spell (α not significantly different from 1), while it is slightly but significantly decreasing for transitions from unemployment to jobs with fixed-term labor contracts (FTC hereafter) and to community jobs (CJ hereafter). These results are in line with the results obtained from the estimation of the piece wise constant hazard model without covariates, but with correction of the stock sampling bias (see Figure 1).

Various covariates such as age, diploma, gender, marital status, health, type of housing, car ownership, regional dummies and previous labor market experience appear to have statistically significant but sometimes opposite effects on the intensities of transition from unemployment. For example, previous experience increases the intensity of transition from unemployment to FTC jobs but reduces very significantly the intensity of transition to community jobs; it has a smaller negative impact on the intensity of transition to "courses for preparation to the working life". Intensities of transition from unemployment to fixed-term labor contracts or to programs are lower for women and low-educated individuals; they decrease with age, with the exception of the category called "other programs".

5.2.2. The propensity scores

Figure 2 presents nonparametric kernel estimates of the distributions of the ratios $\Pi^{l\backslash m}(X_i) = \dfrac{\Pi^l(X_i)}{\Pi^l(X_i) + \Pi^m(X_i)}$ of conditional propensity scores (given the state observed just after the exit from the initial unemployment spell) for each pair of treatments (programs) of interest. For example, in the North-West panel, we plot the distribution of the ratio of the conditional probability to move from unemployment to a job under a fixed-term labor contract (FTC hereafter) over the sum of this probability and the conditional probability to move from unemployment to a community job, for individuals who transited from unemployment to an FTC job (solid line) and for unemployed who effectively moved to to a community job (dashed line).

Several points have to be emphasized. For each pair of programs (treatments) to be compared, it appears that the common supports of the ratios are wide enough, and these common supports differ between pairs of treatments. Moreover, for some pairs, the shapes of the ratio distributions significantly differ. For example, when comparing the relative probabilities of entering a fixed-term contract (FTC) job for individuals who have effectively accepted an FTC job and a community job (see North-West panel, Figure 2), we observe that the distribution of the ratio of propensity scores is more concentrated in the highest part of the support for individuals who have entered an FTC job, while it is more concentrated in the middle for young people who entered a community job. A similar pattern appears when comparing FTC jobs and "courses for preparation to the working life", or "community jobs" and "other programs" (see Figure 2). Here is a potential source of selectivity bias for the naive estimator and a challenging situation for the matching estimator. Under the conditional independence assumption, Figure 2 provides a graphical representation of the upper bound of the naive estimator bias. Indeed we have:

$$
\begin{aligned}
Bias &= E\left(Y_{l,i} \mid T_i = l\right) - E\left(Y_{l,i} \mid T_i = m\right) \\
&= E\left(E\left(Y_{l,i} \mid \Pi^{l\backslash m}\left(X_i\right), T_i = l\right) \mid T_i = l\right) \\
&\quad -E\left(E\left(Y_{l,i} \mid \Pi^{l\backslash m}\left(X_i\right), T_i = m\right) \mid T_i = m\right) \\
&= E\left(E\left(Y_{l,i} \mid \Pi^{l\backslash m}\left(X_i\right)\right) \mid T_i = l\right) \\
&\quad -E\left(E\left(Y_{l,i} \mid \Pi^{l\backslash m}\left(X_i\right)\right) \mid T_i = m\right) \\
&= \int_{Support(X_i)} E\left(Y_{l,i} \mid \Pi^{l\backslash m}\left(X_i\right)\right) \\
&\quad \times \left[f\left(\Pi^{l\backslash m}\left(X_i\right) \mid T_i = l\right) - f\left(\Pi^{l\backslash m}\left(X_i\right) \mid T_i = m\right)\right] dX_i
\end{aligned}
$$

From that equality, we deduce that

$$
\begin{aligned}
|Bias| \;\; & \leq \;\; \underset{X_i}{Max} \left(E\left(Y_{l,i} \mid \Pi^{l\backslash m}\left(X_i\right)\right)\right) \\
& \quad \times \int\limits_{Support(X_i)} \left| f\left(\Pi^{l\backslash m}\left(X_i\right) \mid T_i = l\right) - f\left(\Pi^{l\backslash m}\left(X_i\right) \mid T_i = m\right) \right| dX_i
\end{aligned}
$$

When $Y_{l,i}$ is a dummy variable with possible values 0 or 1, then we have :

$$
|Bias| \leq \int\limits_{Support(X_i)} \left| f\left(\Pi^{l\backslash m}\left(X_i\right) \mid T_i = l\right) - f\left(\Pi^{l\backslash m}\left(X_i\right) \mid T_i = m\right) \right| dX_i
$$

Thus, the absolute value of the bias associated with the naive estimator is bounded by the surface lying between the two distributions shown in each window of Figure 2.

6. Matching Estimates

6.1. The Response Variables and the Matching Algorithm

For evaluating the impact of training programs, we use various response variables. The first one is a dummy variable representing the state occupied by the individual just after the treatment. In our application to French data, this variable has three alternative definitions:

- first, we set it equal to 1 if this state is an LTC (long-term contract) job, an FTC job or a new progam spell, 0 otherwise,
- then, it is set equal to 1 if this state is an LTC job or an FTC job, 0 otherwise,
- finally, it is equal to 1 if this state is an LTC job only, 0 otherwise.

We also consider the same variables 3 months and 6 months after the end of the treatment, which enables us to consider temporal effects. The three others response variables are count data:

- the total number of months spent in LTC jobs during the 6 months following the end of the treatment,

- the total number of months spent in LTC or FTC jobs over the same period,
- the total number of months spent in LTC jobs, FTC jobs or training programs during these 6 months.

Investigations will be conducted on the full common supports of the ratios of propensity scores, but also on their lowest and highest parts to point out potential score effects.

To estimate the average conditional effect of treatment l with respect to treatment m given that individual i is assigned to treatment l, we use a kernel matching estimator such as the ones studied by Heckman, Ichimura, Smith and Todd (1998). More precisely, we estimate the counterfactual parameter $E(Y_{m,i} \mid T_i = l)$ by the Nadaraya-Watson kernel regression

$$y_{m,i}(l) = \frac{\sum_{j=1}^{N} y_j \times 1(T_j = m) \times K\left(\dfrac{\Pi^{l\backslash m}(X_i) - \Pi^{l\backslash m}(X_j)}{h_{N_l}}\right)}{\sum_{j=1}^{N} 1(T_j = m) \times K\left(\dfrac{\Pi^{l\backslash m}(X_i) - \Pi^{l\backslash m}(X_j)}{h_{N_l}}\right)}$$

where $\Pi^{l\backslash m}(X_j) = \dfrac{\Pi^l(X_j)}{\Pi^l(X_j) + \Pi^m(X_j)}$, $K(\cdot)$ is a kernel function,[4] and h_{N_l} is the "rule-of-thumb" bandwith parameter calculated on the support of the ratio $\Pi^{l\backslash m}$ for the individuals assigned to treatment l. Then we form the output difference $y_{l,i}1(T_i = l) - y_{m,i}(l)$ and average it out on i to obtain a nonparametric estimate of the parameter of interest. We also calculate the naive estimator (the simple mean difference) in order to detect the presence of a selectivity bias in our data.

6.2. Results

6.2.1. Relative Effects of the Programs

Tables 2 to 5 present the estimates obtained with the naive and kernel matching procedures for the different response variables we have considered. Those results are given for the whole common support and have to be read as follows. For example, consider the first row and the first column in Table 2, that is the gain in term of probability to be in an LTC job, an FTC job or another program just after the treatment; for a person who was previously in a community job (CJ),

[4] In our application, K is chosen to be the quartic kernel function.

the average loss from not having participated in a CPWL program is estimated as -0.077 (s.e. 0.062) with the matching estimator. The reading is the same for all the remaining tables. Tables 2 to 5 help us to compare the relative effectiveness of the various programs.

When the output variable is the probability to become employed in an LTC job, an FTC job or another progam at the end of program (Table 2), significant effects appear six months after the end of the "treatment". The CPWL program seems to be the most effective program, especially when comparisons are made with the other types of programs or with an FTC job; nevertheless, the probability to be employed after an FTC job is higher than the probability to be employed after a community job or after a program in the "other programs" category. Moreover, for individuals who were hired in an FTC job, the benefit of a non participation in a CJ program is higher than the benefit of a non participation in "other programs". At the opposite, for young people who were in a community job and for the ones who were in a program of the "other programs" category, the losses of not being employed in an FTC job have the same magnitude (-0.08 with s.e. 0.04). Thus "other programs" seem to have given better results than community jobs.

When the output variable is the probability to be employed in an LTC job (Table 4), i.e. in a stable employment state, there are no significant differences between programs. But employment in an FTC job is still more effective than all types of programs, whatever the date is. However, it must be noticed that these effects are stable through time after a CJ job, but are clearly decreasing after a CPWL program or after an "other program". When comparing programs with FTC jobs, we find that "other programs" display the lowest loss six months after the end of the "treatment".

When the output variable is the probability to be employed in an LTC job or in an FTC job (Table 3), there is a positive effect of CJ and CPWL programs vs. "other programs" just after and 3 months after the program, but these effects clearly disappear six months after. The CPWL program is still the most effective program when compared with FTC jobs, since there is no significant negative effect six months after for people who effectively participated in a CPWL program, while such effects exist when FTC jobs are compared with CJ or "other programs":

$$E\left(Y_{CJ} - Y_{FTC} \mid T_i = CJ\right) = -0.136 \quad (s.e.\, 0.049),$$

$$E\left(Y_{Others} - Y_{FTC} \mid T_i = Others\right) = -0.143 \quad (s.e.\, 0.041)$$

but

$$E\left(Y_{CPWL} - Y_{FTC} \mid T_i = CPWL\right) = -0.078 \quad (s.e.\, 0.049).$$

There is an asymmetry between $E\left(Y_l - Y_m \mid T_i = m\right)$ and $E\left(Y_m - Y_l \mid T_i = m\right)$ when comparing FTC jobs and CPWL programs: one is significant while the other is not. For people who were effectively employed in an FTC job, the benefit from being hired in an FTC job rather than participating in a CPWL program is positive; at the opposite, for people who effectively participated in the CPWL program, there is no significant loss from not having found an FTC job. There is no such asymmetry for community jobs and "other programs" (the loss from not having found an FTC job is significantly negative).

When the output variable is the time spent in each of the employment states over the six months period after the program (Table 5), we find that there are no significant differences between the programs. However, employment in an FTC job is associated with significant effects which vary from 0.5 to 0.9: this corresponds to a gain (or a loss for program participants) varying from 2 weeks to one month in employment.

To summarize these first results, we can say that an FTC job is more effective than the employment programs. Among these programs, the most effective one seems to be the CPWL program; the less effective is the CJ program, especially when the output variable is employment in an LTC job or an FTC job. Thus, on-the-job training programs in the private sector (associated with higher amounts of vocational and specific training) give better results than the programs in the public sector. It is also interesting to notice that significant differences between programs appear when the output variables are the probability to be employed in an LTC job, an FTC job or another program, and the probability to be employed in an LTC job or an FTC job, but none is significant when the output variable is the probability to be employed in an LTC job. This result shows that there exists a gap between stable and unstable employment states, and that employment programs are not designed to increase the probability of finding an LTC job but simply to increase the probability of leaving unemployment. Finally, the gain associated with non participation in a program for people who are hired in an FTC job is generally higher (in absolute value) than the loss of not getting an FTC job for people who participate in a program.

6.2.2. Selection Bias

Comparisons between the naive and kernel matching estimates show the presence of some selectivity bias in our data. As it is suggested by the conditional propensity scores distributions in Figure 2, the selectivity bias is present when the score distributions estimated for two subgroups of individuals (for example, the ones who participated in a CPWL program and the ones who were employed in a community job) exhibit significant differences. For instance, consider the output variable "probability to be employed in an LTC job or in an FTC job six months after the treatment" (see the two last columns in Table 3). When estimating the difference between the conditional probability to be employed six months after the end of the treatment for people who participated in a community job (CJ) and the same conditional probability would they have been employed in an FTC job (row 3 in Table 4), the naive estimator gives -0.224 (s.e. 0.042) whereas the kernel matching estimator gives -0.136 (s.e. 0.049), that is half the first one. Another example is the comparison between the CPWL program and an FTC job given a participation in the CPWL program for the same output variable (row 6 in Table 4). Whatever the date is (just after the treatment, three or six months after the treatment), the naive estimator gives a significantly negative effect whose absolute value increases through time, whereas the kernel matching estimator shows that the difference is not statistically significant.

Such biases are also present when the output variable is the total time spent in each of the three employment states during the six months period after the program (Table 5). Those comparisons show the usefulness of kernel matching estimators in attempting to remove selectivity bias.

6.2.3. Heterogeneity across participants in a program

We have previously discussed the relative effects of the different treatments, averaging over all conditional probabilities lying in the common support of each pair of treatments. It is also interesting to study these effects on subintervals of the common support, that is for particular values of the conditional probabilities. This exercise allows us to emphasize the variability of the effects of a program for recipients who have very different conditional probabilities to participate. The first reason is that there is no reason why such effects should be constant among the participants. Moreover, the bimodal conditional distributions we have noticed in Figure 2 could also produce such variations. Finally, in terms of human resource allocation, we may expect that individuals who have higher conditional probabilities to participate in their treatment should significantly benefit from that treatment. On the contrary, we could expect that, at best, people with low conditional probabilities of participation (namely, people who should have participated in another treatment given the values of their observable characteristics), do not suffer too much from that misallocation.

We estimate the average effects over two subintervals, namely the lowest and highest parts of the common supports of conditional propnsity scores. For each pair of treatments, we divide the common support $S = \left[\underline{S}, \overline{S}\right]$ into two equal intervals around the value $\frac{(\underline{S}+\overline{S})}{2}$. Thus, comparisons are conducted for subpopulations that have not necessarily the same size, and, as a consequence, results on the whole common supports cannot be considered as a simple addition of the results on the two subintervals we have constructed.

Such comparisons produce results that lead us to revise our first classification of the programs. Except for "other programs", comparisons between various treatments show that positive effects on the whole common support are usually associated with significant positive effects on the highest part of the support and no significant effect on the lowest part; at the opposite, negative effects on the whole common support are usually associated with significant negative effects on the lowest part of the support and no significant effect on the highest part. Positive effects on the higher part of the support suggest that the highest effectiveness is obtained for individuals who have the highest conditional probability to participate; for example, the positive effects of FTC jobs vs CPWL and CJ programs are obtained for people who have a higher probability to be employed in an FTC job and who are effectively hired in an FTC job. Negative effects on the lower part of the support suggest that costs of misallocation are paid by people who have the lowest probability to enter the treatment they have effectively received. That is the case when we compare CPWL and CJ programs vs FTC jobs for individuals who participated in CPWL or CJ programs but who had a lower conditional probability to do so (notice that people with a higher probability to enter treatment l conditionally to treatments l and m are those who have a lower probability to enter treatment m conditionally to treatments l and m). Thus there is a cost of misallocation. Moreover, our results give a partial idea of what could be a way of improving such an allocation, which is a question of special interest for policy recommendations. For example, when the output variable we consider is the probability to be in a stable (LTC) job six months after the treatment, the loss from not having participated in other programs for people who participated in a CJ program and who had a lower conditional probability to do so is -0.156 (s.e. 0.064), whereas for people who had a higher probability to do so, there is neither loss or gain because the estimate difference is 0.007 (s.e. 0.054). Thus, one way to improve the allocation could be to offer "other programs" than CJ programs to people whose observable characteristics are associated with a lower conditional probability of getting a CJ program. Finally, it should be noticed that due to the fact that our results are pairwise comparisons, different improvements may be proposed to the same person.

As we noticed above, "other programs" seem to be an exception, especially when compared to FTC jobs. Surprisingly, for that pair of treatments, positive effects on the whole common support are associated with positive effects on the lower part of the support, whereas negative effects on the whole support are associated with negative effects on the higher part of the support. More precisely, for people who have a higher conditional probability to participate in other programs,

$$E\left(Y_{Others} - Y_{FTC} \mid T_i = Others\right) = -0.14\ (0.061),$$

whereas for people who have a lower probability to participate in other programs,

$$E\left(Y_{Others} - Y_{FTC} \mid T_i = Others\right) = -0.058\ (0.052)$$

where Y is 1 if the individual is employed in an LTC job six months after the treatment, 0 otherwise. Thus, "other programs" have also a negative signalling effect with respect to FTC jobs. Moreover, this effect is revealed from the first date (just after the treatment), and seems to be constant through time.

7. Conclusions

In this paper we have applied the statistical framework developed by Imbens (1999) and Lechner (1999) to identify and to estimate the causal effects of multiple treatments under the conditional independence assumption. In particular, we have shown that, under this assumption, matching with respect to the ratio of the scores $P\left(T_i = l \mid X_i\right)$ and $P\left(T_i = k \mid X_i\right)$ allows to estimate nonparametrically the average conditional treatment effect $E\left(Y_{l,i} - Y_{m,i} \mid T_i = l\right)$ for a pair of treatments l and m. In our application we have considered the youth employment programs which were set up in France during the eighties to improve the labor market prospects of the most disadvantaged and unskilled young workers. Using data from INSEE previously analyzed by Bonnnal, Fougère and Sérandon (1997), we have re-examined the impact of these programs on the subsequent employment status by implementing matching estimators introduced by Heckman, Ichimura, Smith and Todd (1998) and Heckman, Ichimura and Todd (1998).

Due to the fact that our sample is extracted from the stock of unemployed people at a given date (August 1986), we derived the propensity scores from a competing-risks duration model. This specification allowed us to take rigorously into account the potential endogenous effect of the unemployment duration on the process of assignment to treatments. From the nonparametric kernel estimates of the distributions of the ratios $\Pi^{l\backslash m}(X_i) = \Pi^l(X_i) \Big/ \Big[\Pi^l(X_i) + \Pi^m(X_i)\Big]$ of conditional propensity scores (given the state observed just after the exit from the initial unemployment spell), we observed that, for each pair of programs (treatments) to be compared, the common supports of the ratios are wide enough, and these common supports differ between pairs of treatments. Moreover, for some pairs, the shapes of the ratio distributions significantly differ.

The kernel matching estimates of the mean output differences show the variability of program effects, both between programs and among recipients of the same program. For instance, if the output variable is the probability to become employed in an LTC job, an FTC job or another progam, significant effects appear six months after the end of the "treatment". With respect to this output, the CPWL program seems to be the most effective program, especially when comparisons are made with the other types of programs or with an FTC job; nevertheless, the probability to be employed after an FTC job is higher than the probability to be employed after a community job or after a program in the "other programs" category. However, if the output variable is the probability to be employed in an LTC job, i.e. in a stable employment state, or the time spent in each of the employment states over the six months period after the program, there are no significant differences between programs. On the whole, it appears that an FTC job is more effective than the employment programs. Among these programs, the most effective one seems to be the CPWL program; the less effective is the CJ program, especially when the output variable is employment in an LTC job or an FTC job. Thus, on-the-job training programs in the private sector (associated with higher amounts of vocational and specific training) give better results than the programs in the public sector. This general result confirms the conclusions of the paper written by Bonnal, Fougère and Sérandon (1997), which were deduced from a very different approach.

But our paper contains further results. We have also studied the relative effects of the different programs on subintervals of the common support, that is for particular values of the conditional probabilities. This exercise allowed us to emphasize the variability of the effects of a program for recipients who have very different conditional probabilities to participate. We found that, in general, comparisons between various treatments show that positive effects on the whole common support are usually associated with significant positive effects on the highest part of the support and no significant effect on the lowest part; at the opposite, negative effects on the whole common support are usually associated with significant negative effects on the lowest part of the support and no significant effect on the highest part. Positive effects on the higher part of the support suggest that the highest effectiveness is obtained for individuals who have the highest conditional probability to participate; for example, the positive effects of FTC jobs vs CPWL and CJ programs are obtained for people who have a higher probability to be employed in an FTC job and who are effectively hired in an FTC job. Negative effects on the lower part of the support suggest that costs of misallocation are paid by people who have the lowest probability to enter the treatment they have effectively received. That is the case when we compare CPWL and CJ programs vs FTC jobs for individuals who participated in CPWL or CJ programs but who had a lower conditional probability to do so. Thus our results give a partial idea of what could be a way of improving the assignment of applicants through treatments, which is a question of special interest for policy recommendations: due to the fact that our results are pairwise comparisons, different improvements may be sometimes proposed to the same person.

8. Appendix

- *Proof of Proposition 1*

First we have the following usual relation

$$\begin{aligned} P\left(T_i = l \mid X_i, T_i \in \{l, m\}\right) &= \frac{P\left(T_i = l \mid X_i\right)}{P\left(T_i \in \{l, m\} \mid X_i\right)} \\ &= \frac{\Pi^l\left(X_i\right)}{\Pi^l\left(X_i\right) + \Pi^m\left(X_i\right)} \\ &= \Pi^{l \backslash m}\left(X_i\right) \end{aligned}$$

Similarly we have

$$P\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\right)$$

$$
\begin{aligned}
&= \frac{P\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}\right)}{P\left(T_i \in \{l, m\} \mid X_i, Y_{l,i}, Y_{m,i}\right)} \\
&= \frac{P\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}\right)}{P\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}\right) + P\left(T_i = m \mid X_i, Y_{l,i}, Y_{m,i}\right)} \\
&= \frac{P\left(T_i = l \mid X_i\right)}{P\left(T_i = l \mid X_i\right) + P\left(T_i = m \mid X_i\right)} \\
&= \frac{\Pi^l\left(X_i\right)}{\Pi^l\left(X_i\right) + \Pi^m\left(X_i\right)} \\
&= \Pi^{l\backslash m}\left(X_i\right)
\end{aligned}
$$

where we use the independence property, which directly implies

$$
P\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}\right) = P\left(T_i = l \mid X_i\right).
$$

Then

$$
\begin{aligned}
& P\Big(T_i = l \mid \Pi^{l\backslash m}\left(X_i\right), Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\Big) \\
= \;& E\Big(T_i = l \mid \Pi^{l\backslash m}\left(X_i\right), Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\Big) \\
= \;& E\Big(E\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\right) \mid \Pi^{l\backslash m}\left(X_i\right), Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\Big) \\
= \;& E\Big(P\left(T_i = l \mid X_i, Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\right) \mid \Pi^{l\backslash m}\left(X_i\right), Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\Big) \\
= \;& E\Big(\Pi^{l\backslash m}\left(X_i\right) \mid \Pi^{l\backslash m}\left(X_i\right), Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\Big) = \Pi^{l\backslash m}\left(X_i\right)
\end{aligned}
$$

Similarly we have

$$
P\Big(T_i = l \mid \Pi^{l\backslash m}\left(X_i\right), T_i \in \{l, m\}\Big) = \Pi^{l\backslash m}\left(X_i\right)
$$

From this last equation, we deduce the desired property

$$
P\Big(T_i = l \mid \Pi^{l\backslash m}\left(X_i\right), Y_{l,i}, Y_{m,i}, T_i \in \{l, m\}\Big) = P\Big(T_i = l \mid \Pi^{l\backslash m}\left(X_i\right), T_i \in \{l, m\}\Big) \; \blacksquare
$$

- *Proof of Proposition 2*

Using the independence assumption, we get

$$\begin{aligned} E(Y_{im} \mid T_i = l) &= E(Y_{im} \mid T_i = l) \\ &= E(E(Y_{im} \mid X_i, T_i = l) \mid T_i = l) \\ &= E(E(Y_{im} \mid X_i) \mid T_i = l) \end{aligned}$$

Considering the decomposition of the joint density h of the covariates and the treatments

$$h(X_i, T_i) = f(X_i \mid T_i) \times g(T_i) = f(X_i) \times g(T_i \mid X_i)$$

we obtain

$$\frac{f(X_i \mid T_i)\, g(T_i)}{g(T_i \mid X_i)} = f(X_i)$$

which implies

$$f(X_i \mid T_i = l) = f(X_i \mid T_i = m) \frac{\Pi_l(X_i) \times P(T_i = m)}{\Pi_m(X_i) \times P(T_i = l)}$$

Thus

$$\begin{aligned} E(Y_{im} \mid T_i = l) &= E\left(E(Y_{im} \mid X_i) \frac{\Pi_l(X_i)\, P(T_i = m)}{\Pi_m(X_i)\, P(T_i = l)} \mid T_i = m\right) \\ &= E\left(E\left(Y_{im} \frac{\Pi_l(X_i)\, P(T_i = m)}{\Pi_m(X_i)\, P(T_i = l)} \mid X_i\right) \mid T_i = m\right) \\ &= E\left(E\left(Y_i \frac{\Pi_l(X_i)\, P(T_i = m)}{\Pi_m(X_i)\, P(T_i = l)} \mid X_i\right) \mid T_i = m\right) \\ &= E\left(Y_i \frac{\Pi_l(X_i)\, P(T_i = m)}{\Pi_m(X_i)\, P(T_i = l)} \mid T_i = m\right) \blacksquare \end{aligned}$$

- *Proof of Proposition 3*

$$
\begin{aligned}
& E\left(Y_{l,i}-Y_{m,i}\mid T_i=l\right) \\
= \ & E\left(Y_{l,i}-Y_{m,i}\mid T_i=l, T_i\in\{l,m\}\right) \\
= \ & E\left(Y_{l,i}-E\left(Y_{m,i}\mid \Pi^{l\backslash m}\left(X_i\right), T_i=l, T_i\in\{l,m\}\right)\mid T_i=l, T_i\in\{l,m\}\right) \\
= \ & E\left(Y_{l,i}-E\left(Y_{m,i}\mid \Pi^{l\backslash m}\left(X_i\right), T_i=m, T_i\in\{l,m\}\right)\mid T_i=l, T_i\in\{l,m\}\right) \\
= \ & E\left(Y_{l,i}-E\left(Y_{m,i}\mid \Pi^{l\backslash m}\left(X_i\right), T_i=m\right)\mid T_i=l\right) \ \blacksquare
\end{aligned}
$$

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Table 1: Estimates of the Unemployment Duration Model

Transition to:	FTC jobs		Community jobs		CPWL programs		Other programs	
Alpha	0.860	(0.035)	0.860	(0.057)	1.004	(0.070)	1.062	(0.062)
Intercept	-3.507	(0.178)	-3.397	(0.259)	-4.716	(0.285)	-4.928	(0.286)
Women	-0.262	(0.085)	-		-0.486	(0.156)	-0.148	(0.130)
Married men	0.418	(0.164)	-		-		-	
Married women	-0.732	(0.137)	-1.473	(0.346)	-0.644	(0.282)	-0.678	(0.195)
Age $\leq$ 18	ref.		ref.		ref.		ref.	
Age 19-21	0.188	(0.089)	-		-		0.229	(0.189)
Age 22-23	0.212	(0.101)	-0.947	(0.236)	-0.380	(0.196)	0.524	(0.204)
Age 24-25	-		-1.276	(0.334)	-0.759	(0.265)	0.672	(0.214)
Age 26-27	-		-2.328	(0.718)	-2.077	(0.590)	0.568	(0.254)
Dip1	ref.		ref.		ref.		ref.	
Dip2	0.271	(0.138)	-		-		0.393	(0.185)
Dip3	0.352	(0.105)	-		0.238	(0.186)	-	
Dip4	0.597	(0.122)	0.552	(0.186)	0.428	(0.240)	0.341	(0.200)
Dip5	0.407	(0.208)	0.664	(0.332)	0.797	(0.398)	0.337	(0.284)
Dip6	0.508	(0.190)	0.480	(0.331)	0.965	(0.343)	0.475	(0.292)
Dip7	1.115	(0.190)	-		0.908	(0.472)	0.701	(0.334)
Dip8	0.611	(0.272)	-		-		-1.288	(1.012)
Poor health	-0.219	(0.097)	-		-0.228	(0.188)	-	
Having a car	0.288	(0.094)	0.185	(0.149)	-		-	
Living with parents	-0.125	(0.110)	-		-		-	
Collective housing	0.391	(0.194)	-0.601	(0.515)	-		-	
Regions:								
Nord	-0.615	(0.178)	-		0.759	(0.211)	-0.541	(0.255)
Picardie	-		-0.572	(0.326)	0.539	(0.290)	-	
Lorraine	-0.773	(0.230)	-		-		-	
Basse Normandie	-		1.021	(0.467)	1.068	(0.596)	-	
Bretagne	-		-		0.710	(0.291)	-	
Auvergne	-		-		1.251	(0.299)	0.590	(0.298)

Remarks: between parentheses are the standard errors; educational levels are indicated by dip1 (elementary school), dip2 (junior high school only), dip3 (basic vocational technical shool), dip4 (elementary school and junior high school), dip5 (high school only), dip6 (advanced vocational technical school), dip7 (technical college and undergraduate), dip8 (graduate school and other post secondary education)

Table 1 (continued): Estimates of the Unemployment Duration Model

Transition to:	FTC jobs		Community jobs		CPWL programs		Other programs	
Regions:								
Rhône Alpes	-		-0.547	(0.270)	-		-	
Poitou Charentes	-0.313	(0.238)	-1.074	(0.456)	-		-	
Limousin	-0.425	(0.288)	-		-		0.446	(0.287)
Languedoc	-0.757	(0.273)	-		-		0.575	(0.241)
Ile de France	0.135	(0.129)	-0.767	(0.329)	-		-	
Centre	0.682	(0.149)	-		-		-	
Haute Normandie	0.337	(0.182)	-		0.821	(0.322)	-	
Midi Pyrénées	-0.321	(0.181)	-		0.759	(0.275)	-	
Franche Comté	-		1.244	(0.269)	-		-	
Provence	-		-1.176	(0.507)	-0.864	(0.588)	-0.856	(0.509)
Corse	-		-		-		0.856	(0.509)
Previous State:								
OLF	ref.		ref.		ref.		ref.	
Temp. job (≤3)	0.645	(0.170)	-0.909	(0.509)	-		-	
Temp. job (>3)	0.551	(0.244)	-1.075	(1.003)	-		-0.865	(0.713)
App. contract	0.452	(0.182)	-0.390	(0.302)	-		-	
Program (≤3)	-		-		0.601	(0.292)	0.498	(0.290)
Program (4-6)	-		-		-		-	
Program (>6)	-		-0.510	(0.328)	-		0.379	(0.291)
FTC job (≤3)	0.399	(0.100)	-0.590	(0.211)	-		-0.214	(0.173)
FTC job (3-6)	0.533	(0.140)	-0.835	(0.344)	-		-	
FTC job (7-12)	0.407	(0.153)	-0.648	(0.336)	-1.091	(0.717)	-0.624	(0.343)
LTC job (≤6)	-		-0.756	(0.583)	0.534	(0.389)	-	
LTC job (7-12)	-		-0.529	(0.458)	-		-	
LTC job (13-24)	-		-1.063	(0.461)	-0.404	(0.392)	-0.587	(0.290)
LTC job (>24)	-		-1.946	(0.589)	-		-	

Remarks: the standard errors are given besides the estimates and between parentheses. The previous state is the state just before the first observed unemployment spell; OLF means "out-of-the-labor-force", Temp. job means "temporary job", App. contract means "apprenticeship contract"; between parentheses we indicate the duration of the previous state spell, which is in months.

Table 2: Kernel matching vs naive estimates of the mean differences (output: employment in an LTC job, an FTC job or in a program)

Date:	Just after the prog.		3 months after		6 months after	
	Matching	Naive	Matching	Naive	Matching	Naive
	Community Jobs (CJ)					
CPWL	-0.077	-0.079	-0.006	-0.004	-0.109*	-0.097*
	(0.062)	*(0.055)*	*(0.062)*	*(0.055)*	*(0.057)*	*(0.057)*
OTHER	-0.052	-0.022	0.082	0.088	-0.017	0.024
	(0.063)	*(0.055)*	*(0.059)*	*(0.055)*	*(0.06)*	*(0.057)*
FTC	-0.018	-0.000	0.031	0.027	-0.081*	-0.113**
	(0.052)	*(0.043)*	*(0.05)*	*(0.044)*	*(0.048)*	*(0.043)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	0.095*	0.079	0.015	0.004	0.092	0.097
	(0.057)	*(0.057)*	*(0.053)*	*(0.055)*	*(0.058)*	*(0.06)*
OTHER	0.042	0.039	0.082	0.071	0.08	0.088*
	(0.05)	*(0.053)*	*(0.056)*	*(0.053)*	*(0.054)*	*(0.048)*
FTC	0.055	0.05	0.031	0.021	0.003	-0.034
	(0.051)	*(0.047)*	*(0.05)*	*(0.042)*	*(0.053)*	*(0.047)*
	Other Programs (OTHER)					
CJ	0.057	0.022	-0.046	-0.088	0.017	-0.024
	(0.06)	*(0.055)*	*(0.058)*	*(0.055)*	*(0.056)*	*(0.056)*
CPWL	-0.038	-0.039	-0.072	-0.071	-0.087	-0.088*
	(0.058)	*(0.055)*	*(0.062)*	*(0.053)*	*(0.057)*	*(0.053)*
FTC	0.038	0.042	-0.028	-0.024	-0.081**	-0.087**
	(0.041)	*(0.043)*	*(0.044)*	*(0.042)*	*(0.041)*	*(0.04)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	-0.022	0.000	-0.019	-0.027	0.151**	0.113**
	(0.058)	*(0.047)*	*(0.054)*	*(0.043)*	*(0.055)*	*(0.048)*
CPWL	-0.049	-0.05	-0.027	-0.021	0.027	0.034
	(0.055)	*(0.044)*	*(0.054)*	*(0.043)*	*(0.049)*	*(0.043)*
OTHER	-0.04	-0.042	0.01	0.024	0.077*	0.087**
	(0.042)	*(0.041)*	*(0.041)*	*(0.041)*	*(0.043)*	*(0.04)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors.

Table 3: Kernel matching vs naive estimates of the mean differences (output: employment in an LTC job or an FTC job)

Date:	Just after the prog.		3 months after		6 months after	
	Matching	Naive	Matching	Naive	Matching	Naive
	Community Jobs (CJ)					
CPWL	0.014	0.023	0.011	0.008	-0.038	-0.035
	(0.057)	*(0.054)*	*(0.057)*	*(0.051)*	*(0.058)*	*(0.055)*
OTHER	0.103**	0.087*	0.114**	0.095**	-0.011	-0.005
	(0.051)	*(0.047)*	*(0.057)*	*(0.046)*	*(0.056)*	*(0.05)*
FTC	0.004	-0.031	-0.017	-0.087**	-0.136**	-0.224**
	(0.044)	*(0.037)*	*(0.049)*	*(0.043)*	*(0.049)*	*(0.042)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	-0.01	-0.023	0.009	-0.008	0.051	0.035
	(0.05)	*(0.046)*	*(0.062)*	*(0.059)*	*(0.051)*	*(0.054)*
OTHER	0.091**	0.07	0.089*	0.073	0.052	0.05
	(0.047)	*(0.046)*	*(0.051)*	*(0.051)*	*(0.055)*	*(0.048)*
FTC	-0.022	-0.063*	-0.053	-0.103**	-0.078	-0.149**
	(0.041)	*(0.038)*	*(0.052)*	*(0.046)*	*(0.049)*	*(0.047)*
	Other Programs (OTHER)					
CJ	-0.08*	-0.087*	-0.059	-0.095*	0.055	0.005
	(0.049)	*(0.049)*	*(0.052)*	*(0.05)*	*(0.049)*	*(0.052)*
CPWL	-0.059	-0.07	-0.066	-0.073	-0.059	-0.05
	(0.057)	*(0.047)*	*(0.051)*	*(0.049)*	*(0.061)*	*(0.045)*
FTC	-0.092**	-0.098**	-0.131**	-0.144**	-0.143**	-0.161**
	(0.038)	*(0.035)*	*(0.038)*	*(0.038)*	*(0.041)*	*(0.04)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	-0.014	0.031	0.056	0.087**	0.228**	0.224**
	(0.056)	*(0.041)*	*(0.059)*	*(0.044)*	*(0.053)*	*(0.045)*
CPWL	0.036	0.063*	0.074	0.103**	0.143**	0.149**
	(0.051)	*(0.038)*	*(0.05)*	*(0.042)*	*(0.054)*	*(0.047)*
OTHER	0.096**	0.098**	0.122**	0.144**	0.145**	0.161**
	(0.038)	*(0.032)*	*(0.039)*	*(0.041)*	*(0.044)*	*(0.041)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors.

Table 4: Kernel matching vs naive estimates of the mean differences (output: employment in an LTC job)

Date:	Just after the prog.		3 months after		6 months after	
	Matching	Naive	Matching	Naive	Matching	Naive
	Community Jobs (CJ)					
CPWL	0.009	0.024	-0.012	0.008	-0.006	0.008
	(0.049)	*(0.047)*	*(0.05)*	*(0.04)*	*(0.051)*	*(0.049)*
OTHER	0.046	0.045	0.012	0.009	-0.029	-0.015
	(0.045)	*(0.042)*	*(0.045)*	*(0.041)*	*(0.051)*	*(0.046)*
FTC	-0.116**	-0.152**	-0.088**	-0.13**	-0.111**	-0.15**
	(0.045)	*(0.036)*	*(0.041)*	*(0.034)*	*(0.045)*	*(0.038)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	-0.001	-0.024	0.025	-0.008	0.016	-0.008
	(0.045)	*(0.044)*	*(0.047)*	*(0.045)*	*(0.045)*	*(0.049)*
OTHER	0.038	0.02	0.016	0.004	-0.029	-0.031
	(0.036)	*(0.038)*	*(0.044)*	*(0.047)*	*(0.044)*	*(0.045)*
FTC	-0.117**	-0.158**	-0.087**	-0.111**	-0.102**	-0.132**
	(0.041)	*(0.035)*	*(0.043)*	*(0.038)*	*(0.04)*	*(0.036)*
	Other Programs (OTHER)					
CJ	-0.011	-0.045	0.031	-0.009	0.047	0.015
	(0.042)	*(0.041)*	*(0.044)*	*(0.045)*	*(0.044)*	*(0.04)*
CPWL	-0.012	-0.02	-0.005	-0.004	0.006	0.031
	(0.041)	*(0.04)*	*(0.046)*	*(0.047)*	*(0.053)*	*(0.045)*
FTC	-0.168**	-0.175**	-0.112**	-0.115**	-0.094**	-0.098**
	(0.032)	*(0.032)*	*(0.039)*	*(0.034)*	*(0.038)*	*(0.037)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	0.158**	0.152**	0.129**	0.13**	0.164**	0.15**
	(0.044)	*(0.037)*	*(0.043)*	*(0.038)*	*(0.044)*	*(0.04)*
CPWL	0.163**	0.158**	0.103**	0.111**	0.119**	0.132**
	(0.046)	*(0.036)*	*(0.043)*	*(0.037)*	*(0.048)*	*(0.036)*
OTHER	0.172**	0.175**	0.091**	0.115**	0.08**	0.098**
	(0.035)	*(0.034)*	*(0.035)*	*(0.034)*	*(0.041)*	*(0.034)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors.

Table 5: Kernel matching vs naive estimates of the mean differences (output: number of months in employment)

State:	LTC+FTC+Prog.		LTC+FTC		LTC only	
	Matching	Naive	Matching	Naive	Matching	Naive
	Community Jobs (CJ)					
CPWL	-0.342	-0.359	-0.029	-0.01	-0.031	0.066
	(0.275)	*(0.30)*	*(0.27)*	*(0.278)*	*(0.256)*	*(0.228)*
OTHER	-0.056	0.161	0.37	0.343	0.022	0.061
	(0.282)	*(0.278)*	*(0.276)*	*(0.258)*	*(0.233)*	*(0.204)*
FTC	-0.258	-0.334	-0.405	-0.827**	-0.644**	-0.882**
	(0.249)	*(0.212)*	*(0.252)*	*(0.222)*	*(0.23)*	*(0.193)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	0.363	0.359	0.09	0.01	0.093	-0.066
	(0.306)	*(0.278)*	*(0.282)*	*(0.262)*	*(0.223)*	*(0.244)*
OTHER	0.305	0.335	0.412	0.361	0.008	-0.045
	(0.294)	*(0.293)*	*(0.261)*	*(0.246)*	*(0.22)*	*(0.226)*
FTC	0.003	-0.099	-0.457*	-0.759**	-0.643**	-0.831**
	(0.25)	*(0.224)*	*(0.253)*	*(0.232)*	*(0.226)*	*(0.187)*
	Other Programs (OTHER)					
CJ	-0.049	-0.161	-0.204	-0.343	0.155	-0.061
	(0.316)	*(0.295)*	*(0.253)*	*(0.239)*	*(0.19)*	*(0.203)*
CPWL	-0.446	-0.335	-0.39	-0.361	-0.023	0.045
	(0.313)	*(0.26)*	*(0.281)*	*(0.236)*	*(0.223)*	*(0.214)*
FTC	-0.261	-0.252	-0.831**	-0.901**	-0.758**	-0.773**
	(0.208)	*(0.196)*	*(0.214)*	*(0.203)*	*(0.188)*	*(0.169)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	0.277	0.334	0.596**	0.827**	0.932**	0.882**
	(0.294)	*(0.212)*	*(0.291)*	*(0.208)*	*(0.213)*	*(0.172)*
CPWL	0.024	0.099	0.666**	0.759**	0.804**	0.831**
	(0.266)	*(0.216)*	*(0.265)*	*(0.211)*	*(0.226)*	*(0.195)*
OTHER	0.195	0.252	0.826**	0.901**	0.673**	0.773**
	(0.214)	*(0.203)*	*(0.189)*	*(0.188)*	*(0.188)*	*(0.202)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors.

Table 6: Kernel matching estimates on the highest and lowest parts of the support (output: employment in an LTC, an FTC or a program)

Date:	Just after the prog.		3 months after		6 months after	
	S^-	S^+	S^-	S^+	S^-	S^+
	Community Jobs (CJ)					
CPWL	-0.15	-0.043	-0.009	-0.004	-0.082	-0.121*
	(0.093)	*(0.081)*	*(0.081)*	*(0.076)*	*(0.086)*	*(0.071)*
OTHER	-0.06	-0.05	0.021	0.099	-0.043	-0.009
	(0.097)	*(0.069)*	*(0.101)*	*(0.069)*	*(0.095)*	*(0.067)*
FTC	0.022	-0.059	0.021	0.041	-0.071	-0.092
	(0.062)	*(0.082)*	*(0.064)*	*(0.082)*	*(0.059)*	*(0.077)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	0.065	0.127	0.047	-0.018	0.11	0.073
	(0.074)	*(0.086)*	*(0.07)*	*(0.085)*	*(0.078)*	*(0.087)*
OTHER	0.047	0.037	0.064	0.101	0.02	0.148*
	(0.064)	*(0.082)*	*(0.074)*	*(0.083)*	*(0.071)*	*(0.082)*
FTC	0.032	0.09	0.027	0.036	-0.038	0.066
	(0.052)	*(0.091)*	*(0.053)*	*(0.097)*	*(0.052)*	*(0.094)*
	Other Programs (OTHER)					
CJ	0.062	0.05	-0.091	0.015	0.026	0.005
	(0.069)	*(0.11)*	*(0.064)*	*(0.115)*	*(0.073)*	*(0.119)*
CPWL	0.003	-0.056	-0.081	-0.067	-0.107	-0.078
	(0.087)	*(0.07)*	*(0.079)*	*(0.07)*	*(0.075)*	*(0.072)*
FTC	0.022	0.059	-0.028	-0.028	-0.063	-0.104
	(0.05)	*(0.071)*	*(0.053)*	*(0.066)*	*(0.661)*	*(0.066)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	0.067	-0.04	-0.011	-0.001	0.035	0.174**
	(0.082)	*(0.067)*	*(0.078)*	*(0.069)*	*(0.086)*	*(0.065)*
CPWL	-0.057	-0.048	-0.048	-0.024	-0.039	0.038
	(0.084)	*(0.063)*	*(0.087)*	*(0.061)*	*(0.083)*	*(0.061)*
OTHER	-0.098	-0.019	-0.015	0.019	0.127**	0.059
	(0.061)	*(0.053)*	*(0.072)*	*(0.055)*	*(0.063)*	*(0.055)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors; S^+ (respectively, S^-) denotes the highest (respectively, the lowest) part of the common support.

Table 7: Kernel matching estimates on the highest and lowest parts of the support (output: employment in an LTC or an FTC job)

Date:	Just after the prog.		3 months after		6 months after	
	S^-	S^+	S^-	S^+	S^-	S^+
	Community Jobs (CJ)					
CPWL	-0.011	0.026	-0.031	0.031	-0.085	-0.015
	(0.065)	*(0.072)*	*(0.086)*	*(0.066)*	*(0.071)*	*(0.078)*
OTHER	0.002	0.131**	-0.078	0.167**	-0.215**	0.045
	(0.098)	*(0.054)*	*(0.091)*	*(0.057)*	*(0.082)*	*(0.059)*
FTC	0.03	-0.023	-0.037	0.003	-0.185**	-0.085
	(0.057)	*(0.067)*	*(0.056)*	*(0.072)*	*(0.059)*	*(0.069)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	-0.003	-0.017	0.017	0.001	0.048	0.054
	(0.074)	*(0.076)*	*(0.075)*	*(0.084)*	*(0.077)*	*(0.072)*
OTHER	0.066	0.12*	0.076	0.103	0.014	0.096
	(0.055)	*(0.066)*	*(0.067)*	*(0.083)*	*(0.063)*	*(0.082)*
FTC	-0.037	0.001	-0.073	-0.021	-0.145**	0.025
	(0.054)	*(0.076)*	*(0.06)*	*(0.078)*	*(0.058)*	*(0.072)*
	Other Programs (OTHER)					
CJ	-0.137**	-0.00	-0.175**	0.102	-0.031	0.175**
	(0.054)	*(0.099)*	*(0.056)*	*(0.101)*	*(0.059)*	*(0.082)*
CPWL	-0.088	-0.046	-0.112	-0.046	-0.098	-0.041
	(0.077)	*(0.064)*	*(0.08)*	*(0.069)*	*(0.085)*	*(0.068)*
FTC	-0.12**	-0.055	-0.123**	-0.142**	-0.131**	-0.16**
	(0.051)	*(0.059)*	*(0.047)*	*(0.056)*	*(0.049)*	*(0.069)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	0.014	-0.02	-0.057	0.078	0.038	0.265**
	(0.072)	*(0.062)*	*(0.074)*	*(0.068)*	*(0.08)*	*(0.066)*
CPWL	0.025	0.038	0.01	0.084	0.001	0.167**
	(0.071)	*(0.055)*	*(0.064)*	*(0.052)*	*(0.075)*	*(0.057)*
OTHER	0.026	0.122**	0.114*	0.125**	0.183**	0.131**
	(0.059)	*(0.049)*	*(0.06)*	*(0.053)*	*(0.059)*	*(0.051)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors; S^+ (respectively, S^-) denotes the highest (respectively, the lowest) part of the common support.

Table 8: Kernel matching estimates on the highest and lowest parts of the support (output: employment in an LTC job)

Date:	Just after the prog.		3 months after		6 months after	
	S^-	S^+	S^-	S^+	S^-	S^+
	Community Jobs (CJ)					
CPWL	0.002	0.012	-0.001	-0.017	-0.017	-0.001
	(0.072)	*(0.062)*	*(0.073)*	*(0.065)*	*(0.065)*	*(0.061)*
OTHER	-0.092	0.084	-0.143**	0.055	-0.156**	0.007
	(0.065)	*(0.054)*	*(0.068)*	*(0.056)*	*(0.064)*	*(0.054)*
FTC	-0.123**	-0.109	-0.13**	-0.044	-0.13**	-0.09
	(0.052)	*(0.07)*	*(0.05)*	*(0.065)*	*(0.054)*	*(0.068)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	0.001	-0.004	0.04	0.009	0.029	0.002
	(0.061)	*(0.06)*	*(0.067)*	*(0.062)*	*(0.06)*	*(0.062)*
OTHER	0.005	0.075	0.038	-0.01	-0.045	-0.012
	(0.051)	*(0.066)*	*(0.049)*	*(0.076)*	*(0.056)*	*(0.071)*
FTC	-0.173**	-0.031	-0.105**	-0.06	-0.123**	-0.07
	(0.045)	*(0.076)*	*(0.048)*	*(0.074)*	*(0.046)*	*(0.064)*
	Other Programs (OTHER)					
CJ	-0.086*	0.094	-0.043	0.133*	-0.005	0.121*
	(0.05)	*(0.061)*	*(0.049)*	*(0.072)*	*(0.056)*	*(0.072)*
CPWL	-0.058	0.01	0.013	-0.013	-0.02	0.018
	(0.061)	*(0.053)*	*(0.074)*	*(0.063)*	*(0.08)*	*(0.069)*
FTC	-0.197**	-0.131**	-0.11**	-0.115**	-0.058	-0.14**
	(0.041)	*(0.057)*	*(0.045)*	*(0.059)*	*(0.052)*	*(0.061)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	0.112	0.167**	0.023	0.15**	0.053	0.186**
	(0.07)	*(0.053)*	*(0.065)*	*(0.053)*	*(0.066)*	*(0.052)*
CPWL	0.088	0.176**	0.06	0.111**	0.104	0.121**
	(0.075)	*(0.049)*	*(0.068)*	*(0.052)*	*(0.065)*	*(0.049)*
OTHER	0.106**	0.196**	0.088*	0.092**	0.149**	0.055
	(0.052)	*(0.044)*	*(0.05)*	*(0.045)*	*(0.055)*	*(0.048)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors; S^+ (respectively, S^-) denotes the highest (respectively, the lowest) part of the common support.

Table 9: Kernel matching estimates on the highest and lowest parts of the support (output: number of months in employment)

Date:	LTC+FTC+Prog.		LTC+FTC		LTC only	
	S^-	S^+	S^-	S^+	S^-	S^+
	Community Jobs (CJ)					
CPWL	-0.282	-0.371	-0.077	-0.006	0.006	-0.049
	(0.463)	*(0.386)*	*(0.412)*	*(0.36)*	*(0.352)*	*(0.339)*
OTHER	0.222	-0.133	-0.352	0.57*	-0.707**	0.224
	(0.455)	*(0.355)*	*(0.393)*	*(0.314)*	*(0.298)*	*(0.289)*
FTC	-0.175	-0.345	-0.531*	-0.272	-0.876**	-0.401
	(0.321)	*(0.413)*	*(0.288)*	*(0.386)*	*(0.264)*	*(0.351)*
	Courses for Preparation to the Working Life (CPWL)					
CJ	0.493	0.225	0.241	-0.069	0.194	-0.015
	(0.409)	*(0.455)*	*(0.396)*	*(0.395)*	*(0.32)*	*(0.356)*
OTHER	0.148	0.481	0.228	0.62*	-0.082	0.11
	(0.345)	*(0.486)*	*(0.325)*	*(0.365)*	*(0.276)*	*(0.359)*
FTC	-0.164	0.26	-0.676**	-0.121	-0.845**	-0.33
	(0.292)	*(0.488)*	*(0.306)*	*(0.446)*	*(0.24)*	*(0.351)*
	Other Programs (OTHER)					
CJ	0.161	-0.34	-0.584**	0.325	-0.226	0.685**
	(0.36)	*(0.471)*	*(0.297)*	*(0.502)*	*(0.274)*	*(0.317)*
CPWL	-0.356	-0.48	-0.636	-0.275	-0.162	0.042
	(0.398)	*(0.387)*	*(0.397)*	*(0.334)*	*(0.399)*	*(0.299)*
FTC	-0.202	-0.336	-0.795**	-0.876**	-0.665**	-0.875**
	(0.231)	*(0.34)*	*(0.238)*	*(0.32)*	*(0.227)*	*(0.305)*
	Jobs under Fixed Term labor Contracts (FTC)					
CJ	0.094	0.314	0.103	0.693**	0.279	1.061**
	(0.421)	*(0.352)*	*(0.384)*	*(0.322)*	*(0.375)*	*(0.255)*
CPWL	-0.063	0.039	0.298	0.728**	0.603*	0.837**
	(0.439)	*(0.294)*	*(0.383)*	*(0.299)*	*(0.365)*	*(0.264)*
OTHER	0.253	0.174	0.843**	0.819**	0.776**	0.635**
	(0.307)	*(0.248)*	*(0.298)*	*(0.275)*	*(0.303)*	*(0.255)*

Remarks: * means that the estimated mean difference is significant at the 10% level and ** that it is significant at the 5% level. Between parentheses we report the bootstrapped standard errors; S^+ (respectively, S^-) denotes the highest (respectively, the lowest) part of the common support.

FIGURE 1 : Estimates of the hazard function of the first observed unemployment spell, with and without correction of the stock sampling bias

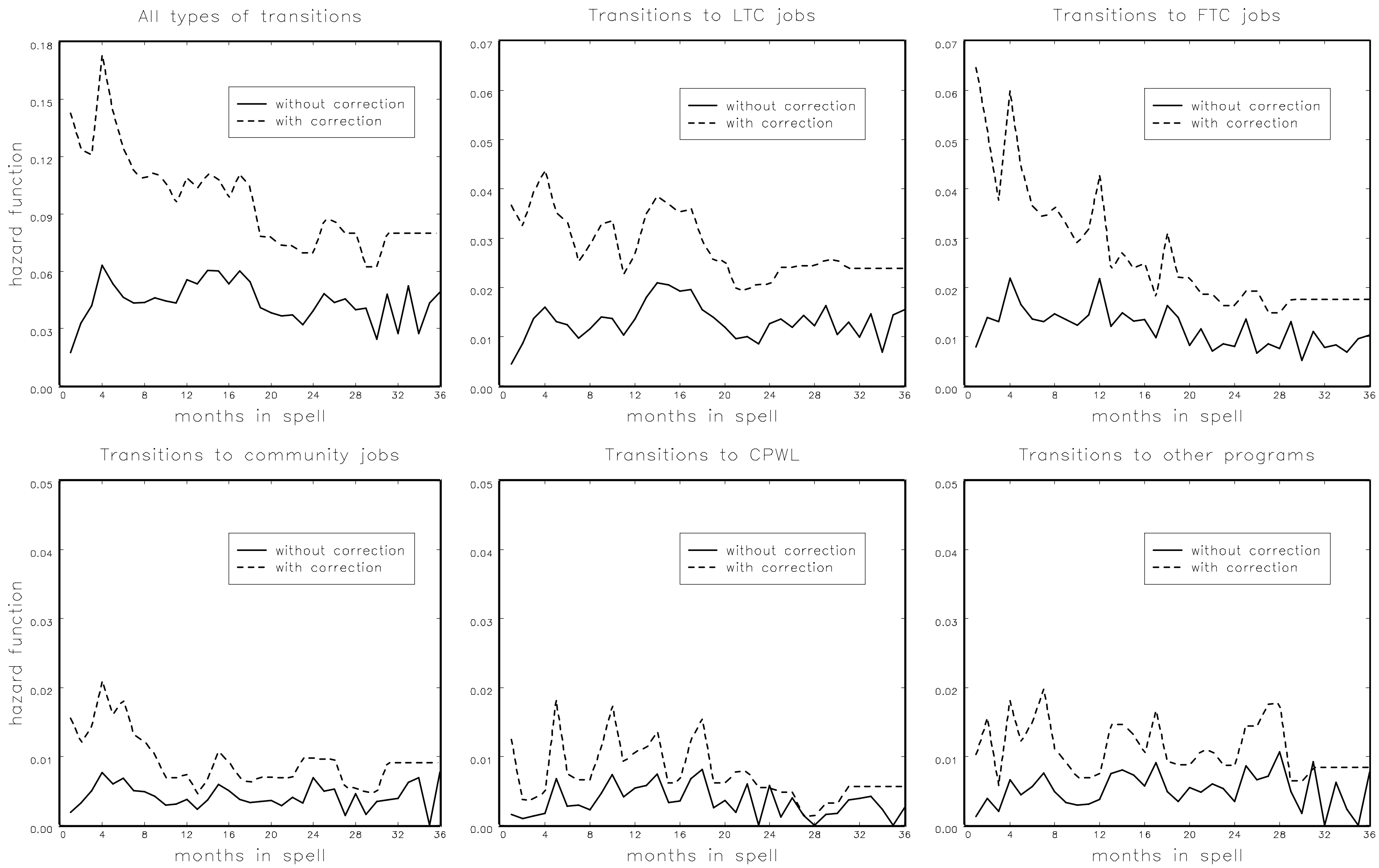

FIGURE 2 : Nonparametric estimates of the density functions of the propensity score ratios, for various pairs of treatments